2007

Effects of contextual socioeconomic stressors on adolescents: mediation and moderation by marital and parent-child relationships

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Effects of contextual socioeconomic stressors on adolescents: Mediation and moderation by marital and parent-child relationships

by

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A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Human Development and Family Studies (Family Studies)

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Ames, Iowa

2007

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ACKNOWLEDGMENTS

First and foremost, I would like to dedicate the completion of my dissertation and graduate program to my wife Minjung and to my children, Emily and Jenna. All of us have sacrificed much and are thankful for what we have been blessed with. I also want to thank our parents, In Bo and Won Hee Jung, and Chul Woong Song and Kyung Ja Jung, for their ongoing support they have given us over the years.

I have been fortunate to have had the opportunity to work with several individuals during my graduate studies who have shaped my research interests and skills. I owe my interest in research methodology and statistics to the following individuals: K. A. S. Wickrama, Fred Lorenz, Jacques Lempers, and Daniel Russell. These individuals taught me to enjoy research and to more deeply appreciate the task of applying statistics to the social sciences. I am amazed when I think about how far I have come from being a clinician to a methodologist. I credit these individuals for introducing me to this exciting new area of scholarship. I also thank Ron Simons for letting me use his dataset from the Single Parent Project for this dissertation.

Finally, I want to thank Dr. Richard Spoth and my colleagues at the Partnerships in Prevention Science Institute (PPSI) for introducing me to the field of prevention science and giving me the opportunity to work on various projects examining the effects of preventive interventions on Iowa families and children. It certainly has been a privilege having this opportunity to transfer my graduate training to practical applications. From Dr. Spoth and my colleagues at PPSI, I have come to a deeper appreciation for applied research, as reflected in Iowa State University's motto, "Science with Practice."

ABSTRACT

This study presents different methods of longitudinal data analysis used to model continuity and change in family research. Innovative modeling techniques such as auto-regressive models, cross-lagged models, latent growth curves, interlocking growth trajectories, latent class growth analysis, and general mixture modeling are used to model the mechanisms in the family stress model. According to the family stress paradigm, negative stressors such as economic stress, work-related stress, and negative life events lead to poor mental health in parents, negatively impact the marital relationship, and undermine effective parenting. In turn, poor parental mental health, marital distress, and ineffective parenting are expected to have a cumulative negative impact on adolescent well-being. The purpose of this study is to explore the mechanisms through which contextual socioeconomic stressors may negatively impact parental and adolescent mental health and undermine effective parenting skills among single-parent mothers. It was expected that the negative effects of these distal stressors on children are mediated through their parents. In addition, this study investigates the possible role of spousal support from the single-mothers' former spouse as moderator of these contextual stressors. Specifically, it was expected that a positive relationship with the former spouse will significantly buffer the effects of these negative stressors on parenting and on the mental health of the single mothers and their adolescent children. The implications of such findings would be that the benefits of positive spousal support may not be limited to married couples. Rather, divorced parents may also benefit from receiving support from their former spouses, particularly in the form of supportive parenting. Hence, the long-term outlook on the well-being and parenting effectiveness of divorced single-parents does not necessarily have to be as bleak as many make it out to be.

CHAPTER 1: GENERAL INTRODUCTION

The dramatic increase in divorce rates in the United States is well-documented. The United States has seen a marked increase in divorce rates in the latter half of the 20th century, with rates increasing precipitously during the 1960s and 1970s, and leveling off in the 1980s, and projections ranging between one-half and two-thirds of recent first marriages ending in divorce (Martin & Bumpass, 1989; Norton & Moorman, 1987). In terms of U.S. per capita (number of divorces per 1,000 people) divorce rates from years 1990 to 2002, rates have declined somewhat from 0.47% to 0.38%, with the latest rate being 0.36% according to the National Center for Health Statistics' (NCHS) most recent National Vital Statistics Reports (Munson & Sutton, 2006). Despite a decrease in the absolute divorce rates in recent years, the ill-effects of divorce remain a reality and have been well-documented.

Divorce is concomitant with a myriad of negative contextual stressors and individual outcome, including negative life events, economic hardship and financial strain, work-related problems, decreased family functioning, and poor physical and mental health (Wallerstein, 1991). Studies have shown that compared to their married counterparts, single parents are at greater risk for psychological problems (Kitson & Morgan, 1990; Rashke, 1987), ineffectual parenting (Hetherington, 1989; McLanahan & Booth, 1989), and have higher rates of both emotional and physical health problems (Amato & Keith, 1991; Bachrach, 1975; Kitson, 1992; Tschann, Johnston, & Wallerstein, 1989; Wickrama, Lorenz, Conger, Elder, Fang, & Abraham, 2006). In consideration of these negative risks, it is not surprising that divorce and single-parenthood are important policy and public health concerns. David Popenoe (1996) aptly put it: "The children of divorced and never-married mothers are less successful in life by almost every measure than the children of widowed mothers…The replacement of death

by divorce as the prime Cause of fatherlessness, then is a monumental setback in the history of childhood" (p. 21).

Negative contextual socioeconomic stressors coupled with troubled family relationships can have a cascading effect on the physical and mental health of adolescent children as well. Many studies have demonstrated that a supportive and warm marital relationship between parents leads to positive parenting practices, which, in turn, may lead to various positive child outcomes, including improved adolescent mental health (Simons, Lorenz, Conger, & Wu, 1992). Conversely, it has been widely established that marital conflict negatively impacts children through diminished parenting practices and parent-child relationships (Cummings & Davies, 2002; Krishnakumar & Buehler, 2000). Summarizing a 30-year review study on the effects of divorce on children, veteran divorce researcher Wallerstein (1991) concluded that divorce not only has acute "brutally painful" effects on a child, but that divorce is a "long-term crisis" that affects the psychological profile spanning an entire generation.

Not only the event of divorce per se, but events surrounding the divorce have a combined negative impact on family members. Most often, economic disadvantage accompanies the divorce event (Holden & Smock, 1991). Consistent with the cumulative advantage/disadvantage (CAD) perspective (Dannefer, 2003; Merton, 1988; e.g., Ross & Wu, 1996), divorce puts children on the higher risk trajectory for long-term negative outcome such as poor health, behavior problems, and crime (Fergusson, Swain-Campbell, & Horwood, 2004). This lifelong pathway to negative outcome usually begins with the economic disadvantages that often accompany divorce (Lorenz, Simons, Conger, Elder, Johnson, & Chao, 1997; Wickrama et al., 2006). Studies have shown that more often than

not, women are the financial victims of divorce, where the children end up in the custody of the mother after divorce and the mothers are left with the childrearing responsibilities with little or no income (Holden & Smock, 1991). It is estimated that more than 85 percent of children whose parents are divorced are in the custody of their mothers (Furstenburg & Cherlin, 1991).

Because of the economic disadvantage of divorced single parents, they have similar risks as those living in poverty. Hundreds of studies have documented the negative effects of poverty on children, many of which have been summarized in recent reports such as *Wasting America's Future* from the Children's Defense Fund and *Alive and Well?* from the National Center for Children in Poverty (Brooks-Gunn & Duncan, 1997; Klerman, 1991). However, there remains a need for precision in disentangling the mechanisms of influence of the various dimensions of poverty on children. One dimension of family relationships that is particularly at risk is the parent-child relationship. For parenting in particular, one study suggests that the sudden loss of income may be a stronger predictor of ineffective parenting rather than the absence of the father. Colletta (1979) sought to determine if differences in the child-rearing practices of divorced and married mothers are related to the father's absence, or if they are largely related to the low income which so often occurs with divorce. She concluded that income was the key factor in determining child-rearing practices rather than the father's absence. As a result of economic hardship, effective parenting usually declines, which eventually leads to physical and mental health problems for the adolescent (Lempers, Clark-Lempers, Simons, 1989; Parke, Coltrane, Duffy, et al., 2004).

According to the most recent Census data, approximately one out of every seven (approx. 14%) families in the United States falls below 125% of the poverty threshold (U.S.

Census Bureau, 2000, Table 760), many of whom are divorced and/or single-parents. A recent analysis of year 2000 Census data indicated that negative child outcomes are highly concentrated in poor families (Mather & Adams, 2006). Negative child outcomes associated with family economic distress include a wide range of problems: poor educational attainment, high rates of school dropout, idleness among teens, physical and mental disabilities, and poor chronic health symptoms (Case, Lubotsky, & Paxson, 2002; Mather & Adams, 2006). Not only does poverty and economic hardship have immediate impact on the lives of children, research has indicated that economic hardship may particularly have long-term negative consequences for adolescents, eventually leading to problems in adulthood (Sobolewski & Amato, 2005).

Considering the potential long-term negative impact of contextual socioeconomic stressors on the family, it is imperative to investigate the mechanisms though which these stressors influence family relationships and identify specific modifiable risk and protective factors. To this end, researchers have examined how the marital relationship between husbands and wives and the parent-child relationship have mediated and moderated the effects of contextual stressors on parenting behaviors (Forehand & Jones, 2003; Wickrama, Lorenz, Conger, Matthews, & Elder, 1997; Simons, Lorenz, Wu, & Conger, 1993; Simons, Lorenz, Conger, & Wu, 1992).

Various models of family stress (Conger, Rueter, & Conger, 1994, 2000; Lavee, McCubbin, & Patterson, 1985; Lempers, Clark-Lempers, & Simons, 1989) have been widely used for modeling the effects of economic hardship on family relationships. According to this general family stress framework, contextual stressors such as negative economic events (e.g., loss of a farm or business) and low income directly lead to economic pressures within the

family. These economic stressors lead to perceived economic pressure, which includes psychologically meaningful events and conditions within the life of the family, such as the inability to purchase basic necessities such as adequate food and medical care that result from economic hardship and that impinge on the emotional health and ongoing relationships of parents. Children and adolescents in the family do not directly experience the risk and adversity created by the hardship; rather, they experience the hardship by the response of the parents to the financial difficulties they face. In other words, the adversity experienced by the children is due to the hardship-related emotions and behaviors of parents. So, contextual stressors indirectly impact the children and adolescents through their parents.

In addition to the mediational processes in the Family Stress Model, another important process in the model is the *moderation* or "buffering effect" (Ensel & Lin, 1991) of social resources. According to the model, social resources such as spousal support and support from friends may reduce or buffer the impact of economic pressure on emotional distress. Social support includes not only tangible objects such as food, housing, and monetary support, but also includes emotional support as well. Statistically, a buffering effect is represented by a significant reduction in the strength of association between two variables, such as economic stress and parenting behavior. A buffering effect of positive social support would, for example, diminish the effect of economic stress so that it no longer significantly predicts ineffective parenting. Examining how multiple risks in the family including both economic pressure and alcohol use or abuse by parents and an older sibling affected risk for the 7th grade target child's alcohol use and abuse, Conger, Rueter, and Conger (1994) demonstrated that a nurturant-involved parenting moderated the relationship between an older sibling's and a younger sibling's (7th grader) alcohol use and abuse. Although buffering

effects are deemed important in the developmental literature on resilience and carry theoretical significance, they are still understudied and are infrequently found in the literature on resilience (Masten, 2001; Luthar, Cicchetti, & Becker, 2000; Ensel & Lin, 1991).

Purpose and Research Questions

Considering the potential long-term negative impact of contextual stressors on the family, the overall goal of this study is to investigate the mechanisms though which these negative contextual socioeconomic stressors influence family relationships and ultimately impact the physical and mental health of parents and adolescents. Adopting the Family Stress Model, this study investigates how the effects of contextual socioeconomic stressors on adolescent mental health are mediated through the mental health of parents and parenting, and through the child's perception of parenting. Also, this study examines how the effects of contextual socioeconomic stressors on the parents' and adolescent's mental health and on the parents' parenting practices may be moderated by social support and the quality of the spousal relationship among both married and divorced parents. By doing so, this study contributes to existing research by examining more closely both the mediational and moderational processes that dictate how contextual socioeconomic stressors impact family functioning and mental health of both parents and children.

Most studies examining the effects of the spousal relationship on parenting have primarily involved married couples. Unfortunately, therefore, our understanding of the role of spousal support among divorced parents is limited due to relatively fewer studies examining the effect of the spousal relationship on parenting practices among divorced or separated couples. Even rarer are studies that have examined how contextual socioeconomic stressors may differentially influence the parenting behaviors of single-parent mothers

depending on the quality of relationship with their former spouse. In this consideration, this study contributes to existing research in three ways:

1. By using a sample divorced single-parent families, this study examines the influence of spousal support of the former spouse on parenting effectiveness among divorced mothers.
2. By using longitudinal panel data for a divorced sample, the mediational and moderational processes as outlined in the family stress model can be modeled so as to more clearly understand the temporal processes and mechanisms of influence.
3. By using new advanced methodological techniques for modeling longitudinal data, aspects of continuity and change in family relationships can be examined with more precision.

Following this framework for research strategy, this study will answer the following research questions:

Question 1: Do contextual socioeconomic stressors such as negative life events, economic stress, and work-related stress have direct long-term impact on the mental health of adolescents?

Question 2: Do parents' mental health and parenting practices mediate the effect of these contextual socioeconomic stressors on adolescents?

Question 3: Do positive social support and spousal support moderate the effects of these contextual socioeconomic stressors on adolescents and their parents?

To address these research issues, this dissertation is organized as follows: Chapter 2 consists of the literature review, describing the overall research model as outlined in the family stress model, and establishing the theoretical foundation that connects the various components of the model: contextual socioeconomic stressors, marital/spousal relationship, parent-child relationship and parenting practices, and individual mental health.

Chapter 3 describes the methodological issues and analytical strategies for answering the research questions posed in this study. A detailed discussion is devoted to comparing and contrasting different methods of longitudinal data analysis.

Chapters 4 and 5 describe the study sample, measures, and results. This study uses a sample of divorced mothers to examine the affects of distal stressors on the mental health of the mother and the adolescent, mediated through ineffective parenting. The unique aspect of this study is that it uses a single-parent mother sample and explores the marital relationship between the mother and her former spouse as a possible buffer of the negative stressors. The aim of the study is to test the hypothesis that a supportive relationship with a former spouse will significantly buffer the negative impact of economic strain on the mother's mental health and parenting effectiveness and also on the adolescent's mental health. Specifically, the more positive support the single mother experiences from her former spouse, the more likely the single-parent mother will exhibit positive parenting practices toward her children, and the more positive the mother and child's mental health will be

Finally, Chapter 6 consists of an overall summary of the dissertation, discusses implications of the study and future direction, and concludes the study.

CHAPTER 2: REVIEW OF THE LITERATURE AND THE GENERAL THEORETICAL MODEL

Overview

Research on the negative impact of harmful environmental stressors on family relationships such as the marital relationship, parent-child relationships, and sibling relationships is well-established. Specifically, previous studies have examined how harmful community environment, neighborhood poverty, low family income, low social support, and social stressors impact parenting behavior in two-parent families (Barrera, Prelow, Dumka, Gonzales, Knight, Michaels, Roosa, & Tein, 2002; Conger, Ge, Elder, Lorenz, & Simons, 1994; Simons, Johnson, Conger, & Lorenz, 1997; Whitbeck, Simons, Conger, Wickrama, Ackley, & Elder, 1997; Wickrama & Bryant, 2003). For example, there is ample research evidence showing that economic hardship has an adverse influence on the psychological well-being of individual family members and on the quality of intra-familial relationships (Conger, McCarthy, Young, Lahey, & Kropp, 1984; Conger et al., 1990, 1991, 1992, 1993; Elder, 1974; Elder, Conger, Foster, & Ardelt, 1992; Liker & Elder, 1983; Whitbeck, Simons, Conger, Lorenz, Huck, & Elder, 1991; Lempers, Clark-Lempers, & Simons, 1989). Wilson (1987, 1991b) has argued that adults living in disadvantaged neighborhoods are likely to be demoralized and to engage in inept parenting. Subsequent studies have supported Wilson's contention and also demonstrated that the effects of financial hardship are exerted indirectly through its influence on parenting and other aspects of the home environment (Conger et al., 1997; Hanson, McLanahan, & Thomson, 1997; McLoyd, Jayaratne, Ceballo, & Borquez, 1994). With increased parental distress, eventually ineffective parenting skills lead to deviant peer affiliations, which, in turn, significantly predict internalizing and externalizing

symptoms among adolescents (Barrera et al., 2002). In addition to negative psychological, social, and behavioral outcomes, children and adolescents growing up in economically disadvantaged community contexts are at risk for negative physical health, mental health, and educational outcome as well (Brooks-Gunn & Duncan, 1997; Brooks-Gunn, Duncan, & Maritato, 1997; Wickrama, Merten, & Elder, 2005).

Considering the potential negative impact of environmental stress on the family, it is imperative to investigate the mechanisms though which these stressors influence family relationships and identify specific modifiable risk and protective factors. To this end, researchers have examined how the marital relationship between husbands and wives have mediated or moderated the effects of environmental stressors on parenting behaviors (Forehand & Jones, 2003; Wickrama, Lorenz, Conger, Matthews, & Elder, 1997; Simons, Lorenz, Wu, & Conger, 1993; Simons, Lorenz, Conger, & Wu, 1992). Many studies have demonstrated that a supportive and warm marital relationship between parents leads to positive parenting practices, which, in turn, leads to various positive child outcomes. However, most studies examining the effects of the marital relationship on parenting have primarily involved married couples; there are relatively fewer studies examining the effects of the spousal relationship on parenting practices among divorced or separated couples. Even fewer studies have examined how environmental stressors may differentially influence the parenting behaviors of single-parent mothers depending on the quality of relationship with their former spouse. In response to the dearth of research in this area, the first aim of this study is to test the hypothesis that a supportive relationship with former spouse will have a significant impact on the single-parent mothers' parenting behaviors. Specifically, the more positive support the single mother experiences from her former spouse, the more positive

parenting practices she will exhibit toward her children. Furthermore, previous studies have shown that mental health is a significant predictor of parenting behaviors (Solantaus, Leinonen, & Punamaki, 2004; Leinonen, Solantaus, & Punamaki, 2002). In this consideration, the second aim of this study is to examine whether social and environmental factors remain significant predictors of parenting behavior even when mental health is included as a predictor variable. Finally, the third aim of this study is to explore the pathways through which distal stressors impact the mental health of children. Previous research has demonstrated how economic problems negatively impact families, and ultimately children (Conger & Elder, 1994; Conger, Rueter, & Conger, 2000; McLoyd, 1998). Consistent with the family stress model developed by Conger, Elder, and colleagues (Conger & Elder, 1994; Conger, Rueter, & Conger, 2000), these studies have demonstrated that economic hardship negatively impacts child outcomes through parental mental health, marital relationship, and parenting behaviors. In accordance with this model, it is expected that the influence of economic stress on adolescent mental health will be mediated through the mother's mental health, relationship with former spouse, and parenting behaviors.

Finally, the fourth aim of this study is to examine whether adolescents' perception of their mothers' parenting mediates the influence of parenting behavior on their mental health. Consistent with attribution theory, behavioral influences operate through perceptions about the behavior. Previous research has suggested that perceived support and consistent discipline of a nurturing family may operate as potential protective factors against negative outcomes (Larzelere & Patterson, 1990; Lempers, Clark-Lempers, & Simons, 1989). In accordance with these findings, the adolescents' perception of their mothers' parenting have

been included in the model. It is expected that perceived parenting will significantly mediate the influence of parenting behavior on adolescent mental health.

The identification of these intra-familial mechanisms may eventually lead to the identification of modifiable risk and protective factors. These findings may have implications in the development of prevention and intervention programs that decrease risk factors and increase resilience among families.

Socioeconomic Determinants of Health and Well-Being

Mechanisms linking contextual socioeconomic stressors to individual health have been conceptualized in terms of SES-related socioeconomic factors and the health gradient (Adler, Boyce, Chesney, Folkman, & Syme, 1993; Miech, Caspi, et al., 1999). According to this framework, individual health trajectories are determined by background factors such as SES and education. The idea is that those who are disadvantaged in terms of SES, income, and education, can expect to experience poor health and perhaps earlier mortality than those who are better-off. However, these gradients are not solely determined by proximal environmental factors such as access to health care or health behavior; rather, it requires a more comprehensive assessment of contextual influences, including factors such as living environment, work environment, social relationships, the larger community setting, and individual knowledge and practice of health behaviors (e.g., personal hygiene, diet, exercise, use and abuse of substances). In order to do this we must move from groups to individuals and understand how behavior and biology interact (Adler, Boyce, Chesney, Cohen, Folkman, Kahn, & Syme, 1994; Adler et al., 1993; McEwen & Seeman, 1999).

Allostasis and Allostatic Load

McEwen and Seeman (1999) suggested that the word "stress" is often overused, particularly in reference to biological factors, and has essentially become an ambiguous term. Instead, they argue, stress is more comprehensive and includes many aspects of lifestyle and daily experience and behavior, including the adjustments to the circadian light-dark cycle. Because the subjective experience of stress does not always correlate with the output of physiological mediators of stress, McEwen and Seeman (1999) argue that a more comprehensive term for the role of biological mediators in adaptation and maladaptation of the individual to the circumstances of life is needed.

Rather than referring to everything dealing with responses to environmental and psychosocial situations as "stress," two new terms, *allostasis* and *allostatic load*, have been suggested as a better alternative (McEwen & Seeman, 1999). Allostasis, meaning literally "maintaining stability (or homeostasis) through change," was introduced by Sterling and Eyer (1988) to describe how the cardiovascular system adjusts to resting and active states of the body. Allostatic load refers to the wear and tear that the body experiences due to repeated cycles of allostasis as well as the inefficient turning-on or shutting off of these responses (McEwen, 1998; McEwen & Stellar, 1993).

The concept of allostasis and allostatic load envisions a cascade of cause and effect that begins with primary stress mediators. Essentially, there is a cascading effect of genetic predisposition and early developmental events, such as abuse and neglect or other forms of early life stress, to predispose the organism to over-react physiologically and behaviorally to events throughout life. In responses to various stress mediators, the body adapts by striving

towards allostasis (i.e., stability or homeostasis). In turn, this constant cycle of turning on and turning off responses leads to cumulative effects over long time intervals (allostatic load).

Many of the same considerations apply to behavioral, as opposed to physiological, responses to challenge, and there are also protective and damaging aspects to one's behavior. Individuals can act to increase or decrease further risk for harm or disease - for example, antisocial responses such as hostility and aggression vs. cooperation and conciliation; risk taking behaviors such as smoking, drinking, and physical risk-taking vs. self protection; poor diet and health practices vs. good diet, exercise, etc. The linkage of "allostasis" and "allostatic load" applies to behavioral responses as well to physiological responses to challenge in so far as the behavioral response, such as smoking or alcohol consumption, may have at least perceived adaptive benefits in the short run but produce damaging effects in the long run.

Genetic Influences

Research examining genetic determinants of health has grown dramatically in recent years due to the advances in genome mapping and bioinformatics. Of particular interest, social researchers of social determinants of health have recognized the direct impact of genetic and physiological causes of health (Caspi, McClay, Moffitt, Mill, Martin, Craig, Taylor, & Poulton, 2002; Caspi, Sugden, Moffitt, Taylor, Craig, Harrington, McClay, Mill, Martin, Braithwaite, & Poulton, 2003). Extensive twin studies have consistently demonstrated how diseases, physical conditions, and mental illnesses have a large genetic component. Certain health conditions such as obesity and diabetes have genetic predispositions, yet its expression can be controlled by behavior and environmental influences. Despite the strong genetic determinants, social research has shown that there

remain significant social determinants of health, net of the effect of genetics and physiology. For example, Wickrama, Lorenz, and Conger (1997) illustrated how health is also determined through the mechanisms of personal characteristics, family relationships, and social relationships. Even distal influences such as family of origin and contextual factors have impacted health. Direct proximal causes of health include malleable lifestyle factors such as risky behaviors, faulty health beliefs and misinformation, and poor physical behaviors such as overeating, malnutrition, and inactivity. Lifestyle changes can directly impact health. For example, studies have demonstrated that obesity and subsequent risk for heart disease can be prevented by simply changing a person's lifestyle, such as keeping physically active and changing one's eating habits (Esposito, Pontillo, Di Palo, Giugliano, Masella, Marfella, & Giugliano, 2003). It is the individual decision made in response to life events, which ultimately determines the health trajectory. On the other hand, life events consists of most non-malleable influences such as normative and non-normative events (i.e., pubertal changes, loss in job, wars, divorce, death of family member, physical accident, etc.), and SES-related factors. These life events comprise "turning points" in the life course, which have the potential to send one's life course into a negative spiral or boost one's physical and mental well-being.

Socioeconomic Status and the Health Gradient

A growing body of literature has closely examined the relationship between socioeconomic status and health outcomes. For example, Wickrama, Conger, and Abraham (2005) demonstrated that family of origin adversity contributed to the impaired mental and physical health of adolescents. Specifically, the influence of family of origin adversity was largely mediated through adolescents' disrupted transition to young adulthood. Furthermore,

level and change in both mental and physical illnesses independently contributed to young adult adversity. Also, levels of physical health problems influenced changes in mental disorders. This study demonstrated that the processes that account for the transmission of socioeconomic adversity from one generation to the next occur through mental disorder and physical illness. The socioeconomic status in the family of origin influence changes in both mental and physical illnesses, which are also associated with subsequent young adult adversity.

The link between SES and health can be understood using the *selection* versus *causation* paradigm. For example, Miech, Caspi, Moffit, Wright, and Silva (1999) examined the link between SES and mental illness of parents and children. They proposed two main ways that SES and mental illness can relate to each other. One way is that SES could directly cause mental illness. Low socioeconomic status and SES-related disadvantages have been linked to poor health. It is possible that individuals in low SES do not have the resources to provide nutritious food, opportunities to engage in various physical activities, nor the knowledge of good health practices. In addition, disadvantaged individuals are exposed to various environmental toxins, limited access to quality health care service facilities, or simply do not have money for health care. One concrete example is where an individual, living in the city, cannot afford a car, so he/she just walks to the nearest place to buy food (usually a convenient store), which usually consists of junk food, fast food, and various poor-quality snack-foods, rather than fresh vegetables, organic goods, and fresh meats.

Another mechanism for explaining the link between SES and health is the *selection* model. According to Miech et al. (1999), the selection (or consequence) view is where individual characteristic such as mental illness causes a downward “spiral of perniciousness,”

which eventually leads to further and further behavioral, mental, and most importantly social problems. Thus, according to the selection view, mental disorders may cause downward mobility among adults and lead them to "drift" into the lower socioeconomic strata. Health problems may be transmitted across generations, and mental illnesses may be transmitted to offspring. The inherited mental illness, then, acts as a cap or a maximum possible level of attainment for the individual. Mental disorders, then, can have cumulative effects across subsequent generations, ultimately leading to the creation of a "residue" of people with mental disorders in the lower socioeconomic strata through the ongoing "cycle of disadvantage" (Miech et al., 1999).

Cumulative Disadvantage of Social Adversity and Health

Cumulative disadvantage is a lifecourse concept referring to the ongoing influence of earlier disadvantages on subsequent disadvantages (Hatch, 2005; Merton, 1988, 1968). Merton (1968) initially introduced the concept of cumulative advantage to explain inequality in productivity and recognition among scientists. According to this concept, inequality results from the unequal distribution of resources supporting productivity, with recognition leading to further productivity, and increasingly working to the advantage of few and the disadvantage of most. The idea is consonant with the saying, "success breeds success" or "wealth begets wealth." For example, a person who performs well receives recognition. Then, in turn, this recognition gives a push to perform even better and more often in the future. In other words, early events set the individual's life course on a certain trajectory. The assumption is that this trajectory is represented by a monotonic linear or curvilinear increase or decrease—there is no change in direction. Thus, a negative event in earlier stages of life can potentially set the individual's life course on a downward trajectory, leading to further

and further problems and disadvantages. Contributors to cumulative disadvantage, O'Rand (1996) argues, consist of both gender inequalities and structural (institutional) inequalities. For example, it is argued that the way income levels (i.e., salary structures), benefits (i.e., insurance), pension plans, and various economic institutions are set up, systematically discriminates against minorities and women (Krieger, 2000; O'Rand, 1996). Thus, an interaction between institutional/structural factors and individual characteristics evolve into a series of disadvantages which accumulate over time. The negative social implication of the cumulative advantage/disadvantage is that it leads to a bifurcation in social structures. In other words, the rich get richer and the poor get poorer. O'Rand notes that minorities are especially prone to persistent, perpetual poverty. Government assistance have been made to alleviate poverty and break the cycle of cumulative disadvantage, however the current state of affairs is that more needs to be done to address the cumulative advantage/disadvantage among women, minorities, and elderly.

Because good health begins early in life (Repetti, Taylor, & Seeman, 2002), the task of identifying sources of cumulative adversity and protective resources across the life course is paramount in understanding health inequalities (Hatch, 2005). Across the life course, cumulative advantage in the form of protective resources may have beneficial results in terms of individual mental and physical health. However, by the same token, cumulative adversity may have serious negative impact on the mental and physical health over the life course by increasing the risk for certain illnesses. This cumulative process is life-long and may vary depending on the conditions (including both adversities and advantages), and by varying responses to these conditions (Pearlin & Skaff, 1996). Depending on early risks and advantages, divergent trajectories may result in health inequalities. Ultimately, the interaction

between individual experience and behavior and the context (life events, circumstances, institutional arrangements) determines whether the individual's life course unfolds to their benefit or disadvantage (O'Rand, 1996). Hence, understanding the interplay between the individual and his/her context is critical to understanding health inequalities. In particular, it requires paying attention to the persistent effects of social statuses (e.g., socioeconomic status [SES] of origin, race/ethnicity, gender, and age) and sources of cumulative adversity and protective resources leading to diverging trajectories and heterogeneity within cohorts across the life course (Kerckoff, 1993; O'Rand & Henretta, 1999).

Marital Relationship and Health

As previously discussed, an extensive body of literature has compared divorced and married couples and has concluded that divorced couples are at greater risk for poorer mental and physical health than their married counterparts. In addition, studies have shown that divorce is concomitant with a myriad of negative contextual socioeconomic stressors and individual outcome, including negative life events, economic hardship and financial strain, work-related problems, decreased family functioning, and poor physical and mental health (Lorenz, Wickrama, Conger, & Elder, 2006; Wallerstein, 1991). Studies have shown that compared to their married counterparts, single parents are at greater risk for psychological problems (Kitson & Morgan, 1990; Rashke, 1987), ineffectual parenting (Hetherington, 1989; McLanahan & Booth, 1989), and have higher rates of both emotional and physical health problems (Amato & Keith, 1991; Bachrach, 1975; Kitson, 1992; Tschann, Johnston, & Wallerstein, 1989). In consideration of these differences between divorced and married individuals, it is possible that mechanisms of influence of socioeconomic stressors on health may differ across the two populations as well. To examine differences in mechanisms of

influence, the present study will compare a sample of divorced single-parent mothers to a sample of two-parent families.

Negative contextual socioeconomic stressors coupled with troubled family relationships can have a cascading effect on the physical and mental health of adolescent children as well. Many studies have demonstrated that a supportive and warm marital relationship between parents leads to positive parenting practices, which, in turn, may lead to various positive child outcomes, including improved adolescent mental health (Simons, Lorenz, Conger, & Wu, 1992). Conversely, it has been widely established that marital conflict negatively impacts children through diminished parenting practices and parent-child relationships (Cummings & Davies, 2002; Krishnakumar & Buehler, 2000). Summarizing a 30-year review study on the effects of divorce on children, veteran divorce researcher Wallerstein (1991) concluded that divorce not only has acute "brutally painful" effects on a child, but that divorce is a "long-term crisis" that affects the psychological profile spanning an entire generation.

Psychological well-being can especially be negatively impacted through the loss of a support system. For men, especially, marriage offers a sense of social support. Studies have demonstrated that the death of a spouse is rated as among the most stressful life event that humans experience (Holmes & Rahe, 1967). Negative impact of the loss of a spouse has been widely studied, however fewer studies have focused on health outcomes of marriage (i.e., physical health and health behaviors). It has been suggested that one mechanism through which the loss of a spouse may negatively impact health is that the loss of a spouse results in the loss of a person who assists in practical day-to-day activities, such as monitoring one's eating habits, personal hygiene, and offering attempts to improve one's health behaviors

(Gove, Styles, & Hughes, 1990). Major life events such as widowhood are also associated with a disturbance in one's normal routine (including participation in health behaviors) and an increase in stress (Holmes & Rahe, 1967).

Despite the recent advances in research on marital relationships and individual mental and physical health, the mechanisms of causal influence remains a mystery. It must be acknowledged that the relationship between marriage and physical health is one of dynamic reciprocity and systemic interdependence (Lorenz & Hraba, 2004; Wickrama, Lorenz, & Conger, 1997). In this case, the causal order must be assumed, based on theory, and carefully examined to identify the direct and indirect effects. Examining the connection between marital stress and physical health, Lorenz and Hraba (2004) found that indeed chronic marital instability has negative consequences for physical health, most of which was mediated through psychological distress.

Social Selection, Social Causation, and Social Interaction in Family Research

The framework of *selection* versus *social causation* (or *strain*) is a traditional approach which may offer one perspective for understanding the problems often associated with single-parent families (Kitson & Morgan, 1990). According to this paradigm, the *selection* process is very much similar to the Darwinian idea of natural selection, whereby either death or adaptation occurs until the organism (or species) eventually survives and settles in its "ecological niche." According to this idea, there are certain characteristics and resources of the organism that predisposes the organism to respond differently to various environmental stressors. Thus, the organism that cannot survive in a certain setting will have to adapt, change settings or face extinction. In terms of human development, selection means that there are individual characteristics that not only predisposes them to a certain behavior or

lifestyle, but may directly cause certain individual (behavioral and mental health) and social outcomes (i.e., low SES). For example, in their study on the relationship between low socioeconomic status and mental health disorders, Miech et al. (1999) defined *selection* as the case where individual level characteristics (i.e., mental health disorders) determines who gets ahead in society. In essence, mental health disorders cause a certain life trajectory—here mental health disorders cause a downward mobility among individuals and drift them into the lower socioeconomic strata. Selection process is a life-long process, whereby, for example, mental disorders are transmitted within generations through a growth trajectory ("cumulative process") and also across generations through genetic transmission as well as through socialization processes ("cycle of disadvantage").

In contrast to selection, *causation* assumes that there are social determinants of individual-level characteristics. Using the example of SES and mental health again, causation would be the case where low SES *causes* one to develop certain mental health disorders. For example, Miech et al. (1999) define *causation* in terms of SES-related adversity damaging psychological functioning. For example, low SES directly causes mental illnesses (i.e., depression and anxiety). Miech et al. (1999) take the definition of causation a step further and include the case where the social characteristic functions as a catalyst. For example, low SES may not only directly cause mental illness but also lead to the emergence of disorders for individuals who already have a genetic disposition for mental disorders.

More recently, however, research has suggested a third perspective for understanding the relationship between socioeconomic stress and individual well-being in addition to the selection and causation perspectives: The interactionist approach (Conger & Donnellan, 2007). According to this perspective, the relationship between social position and life course

development is highly dynamic and suggests an approach that incorporates both the social causation and social selection processes. Conger and Donnellan (2007) cite two studies that provide preliminary support for this perspective. According to the first study, Schoon et al. (2002) investigated the long-term effects of social disadvantage on academic achievement and on subsequent attainments in adulthood. Specifically, they showed that low SES in a child's family of origin predicted lower academic achievement and continuing life stress across the years of childhood and adolescence. Children's lower academic competence and higher life stress, in turn, were associated with lower SES when the children reached their adult years (Schoon et al., 2006; Conger & Donnellan, 2007). In the second study, Wickrama and colleagues (2005) found that low SES in the family of origin predicted adverse economic and related life circumstances for adolescents. These events increased risk for both mental and physical health problems during the transition to adulthood which, in turn, predicted economic problems and poorer social circumstances during the early adult years. Thus, consistent with the interactionist perspective, both studies suggest a reciprocal process in which early SES predicts personal characteristics of children that influence their SES in adulthood. Conger and Donnellan (2007) note, however, that the limitations of these two studies is that these findings could be explained by the social selection argument that parental characteristics may have led to SES in the family of origin and to the course of children's development. Hence, to lend further support for the interactionist perspective, a study by Miech and colleagues (1999) showed that antisocial youth experience lower educational attainment which, in turn, increases risk for further antisocial behavior as a young adult. In this case, it may be that both the SES and ongoing behaviors of these young adults would affect the development of their children.

Selection and Social Causation and the Relationship Between Marital Status and Physical/ Emotional Health

Research on marriage and marital quality wrestles with the question of selection and causation with respect to individual health. For example researchers have found that single parenthood leads to poor mental and physical health (Evenson & Simon, 2005; Lorenz, Wickrama, Conger, & Elder, 2006; Wickrama et al., in press). Turner, Wheaton, and Lloyd (1995) argued that through social causation, divorce creates conditions that make women more vulnerable to stressful and negative life events. Specifically, poor marital quality can directly cause poor health through mechanisms such as directly influencing poor health behaviors, shaping poor health behavioral orientation, and through negative life events. In sum, poor marriage impacts negative health outcomes directly and indirectly through various proximal causes. On the other hand, it can be argued that individuals with certain mental illnesses select themselves into situations of poor marriage and poor marital quality. For example, Patterson and Dishion (1988) argued that individuals with antisocial disorder will select themselves into relationships characterized by stress and further mental illness, thus eventually leading to divorce. Paul Amato (2000) cites research from Patterson and associates illustrating how mothers' antisocial personalities explain the association between mothers' marital changes and behavioral problems in their sons. Amato and Booth's (2001) previous research has also shown that many of the problems in parent-child relationships and child behavioral problems were already present many years prior to divorce. This can be simply explained by the fact that there are dysfunctional family relationships that may exist since marriage that may eventually lead to subsequent divorce, as the "persistent problems" model will show. However, Amato (2000) cautions that pre-existing problems may not

necessarily support the selection hypothesis since studies controlling for pre-existing problems have demonstrated the unique net effects of divorce on post-divorce problems.

Both of these mechanisms can be at work, as evidenced by research (cf. Conger & Donnellan, 2007; Conger et al., 1991; Patterson, Reid, & Dishion, 1982). A more recent closer examination of both the selection and causation models showed more support of the causation process whereby divorced women reported initial extremely high levels of stress following a divorce event (Lorenz et al., 1997, 2006). Eventually, the negative effects of divorced declined, but never to equal levels of well-being at those women who never experienced divorce. In support of the selection perspective, it can be argued that the divorced women already had elevated pre-existing levels of mental illnesses (i.e., depression). However, the study showed that this was not the case. The women in the single-parent study did not differ from the married women in the Iowa Youth and Families Project on their levels of depression and psychological well-being. Nonetheless, the results show support for the causation process, whereby divorce leads to the creation of negative family life events, which in turn lead to increased levels of stress. An analysis with structural equation modeling showed a directly link from levels of stressful events to levels of depression. These results showed that divorce does indeed cause disruptive family environment, which in turn, causes experiences of negative stress. However, contrary to the idea of "cycle of disadvantage" women who had experienced divorce reported a subsequent decline in the levels of experienced negative stress—it did not lead to women experiencing a perpetual state of chaos.

On the other hand, in support of the selection process concept, there were significant effects of pre-existing levels of antisocial behavior to depression and stressful life events.

These results indicate that women with a history of antisocial behavior are prone to future problem behavior and development of mental illness. In terms of long-term intra-generational and intergenerational process, divorce can negatively impact future marriages (as evidence by their even greater rates of divorce among remarried couples) and divorce can negatively impact parenting. A combination of a negatively-charged family environment and poor parenting practices will impact parent-child relationships and subsequent developmental trajectories of the children. However, the implication of this is that subsequent negative effects of divorce on children can be counteracted, buffered, or prevented through positive parenting practices and positive marital relationship (Lorenz et al., 2006; Popenoe, 1996; Simons, 1996).

Modeling Selection and Social Causation

As noted by Kitson and Morgan (1990), a persistent problem in interpreting findings on marital status and health is that studies are often cross-sectional, population-based surveys including people separated and divorced for varying lengths of time and omitting those of the divorced group who remarried or who died. Hence, it is difficult to disentangle issues of selectivity, time since separation, and the impact of post-divorce events. Cross-sectional results do not allow researchers to infer causal links; that is, it does not capture variations across time. Studies using cross-sectional designs have been largely correlational in their analysis. The limitation is that correlation does not infer causation. On the other hand, cross-sectional studies are useful for detecting point-in-time group differences (i.e., inter-individual change).

The advantage of a prospective panel design, on the other hand, is that it allows the researcher to track intra-individual level changes over time, and is one of the criteria for

making statements of causation (i.e., "change in variable X *causes* change in variable Y"). Longitudinal designs allow researchers to capture intra-individual changes over time. In panel studies, data are collected on the same attribute at two or more well-defined points in time, and change is measured by observing the differences in respondents between the time points. A variety of methods have been used to model change in family research (see Lorenz, Wickrama, & Conger, 2004), such as: MANOVA and MANCOVA, autoregressive, and latent growth curve (LGC) modeling.

One approach to specifying the mechanisms that influence health status is to link psychological and physiological measures that highlight the increased risk of illness because of suppressed immunological functioning in stressful conditions such as divorce (Kiecolt-Glaser et al., 1987; Kitson & Morgan, 1990). For example, the causation hypothesis posits that changes in family structure (i.e., divorce) cause elevated levels of psychological distress. Hence, the best way to conduct studies examining causal changes over the life course is to have a prospective, longitudinal design which also includes psychological and physiological measures at later time points, preceded by earlier measures of risk and adversity (e.g., The Family Stress Model; Conger & Conger, 2002).

As an example, Lorenz et al. (1997, 2006) used latent growth curve modeling, directly linking divorce to stressful events and psychological distress, representing the pathways consistent with the social causation hypothesis. According to the social causation hypothesis, divorce creates conditions that make women susceptible to more stressful life events (Turner et al., 1995), and therefore higher levels of distress. The specific hypothesis is that marital status (married vs. divorce) will predict both the level of psychological distress as well as changes in level of psychological distress.

By including another extraneous variable, antisocial behavior, it allows the researcher to test the selection hypothesis. According to the selection hypothesis, women with a history of antisocial behavior are likely to experience more stressful events, become depressed, and are more likely to be among the divorced (Patterson & Dishion, 1988). To model this, a measure of antisocial behavior is included in the model with direct links to level and change in stressful events. This allows the researcher to test the hypothesis that individuals select themselves into stressful situations.

Research has not been conclusive on the matter of social causation versus selection. To date, existing research seems to provide evidence for both processes at work (Conger & Donnellan, 2007; Lorenz et al., 1997; Turner et al., 1995; Wade & Pevalin, 2004). Nonetheless, a carefully-designed model which accounts for both prior selection as well as longitudinal outcome addresses many of the weakness of existing studies.

Summary of Literature Review & Research Needs

Negative contextual socioeconomic stressors coupled with troubled family relationship can have a cascading effect on the physical and mental health of parents and adolescents. Often, economic disadvantage accompanies the divorce event (Holden & Smock, 1991). Consistent with the cumulative advantage/disadvantage (CAD) perspective (Dannefer, 2003; Merton, 1988; Ross & Wu, 1996), divorce puts children on the higher risk trajectory for long-term negative outcome such as poor health, behavior problems, and crime (Fergusson, Swain-Campbell, & Horwood, 2004). This lifelong pathway to negative outcome usually begins with the economic disadvantages that often accompany divorce (Lorenz, Simons, Conger, Elder, Johnson, & Chao, 1997; Wickrama et al., 2006). Considering the potential long-term negative impact of contextual socioeconomic stressors on the family, the

goal of this study was to investigate the mechanisms though which these stressors influence family relationships and identify specific modifiable risk and protective factors.

To model the mechanisms of influence, the present study adopted a model of family stress and adaptation, or the "family stress model" (Conger, Rueter, & Conger, 2000; Lavee, McCubbin, & Patterson, 1985). According to the family stress model (Conger et al., 2000), contextual stressors such as negative economic events (e.g., loss of a farm or business) and low income directly lead to economic pressures within the family. Children experience hardship by the response of the parents to the financial difficulties they face. In other words, the adversity experienced by the children is due to the hardship-related emotions and behaviors of parents. In this way, contextual stressors indirectly impact the children and adolescents through their parents. It is expected that social support and support from the former spouse will buffer the negative influence of socioeconomic contextual stressors on parents and adolescents. These pathways will be explored in detail in the following chapters.

The review of existing literature revealed several areas that remain to be addressed by future research:

- Need for a longitudinal analytic approach examining the family stress model in its entirety;
- Need for advanced techniques for modeling longitudinal change (residual and mean level changes), reciprocal family processes, and sub-population heterogeneity;
- Need for the inclusion of the individual's perception in predicting outcome behaviors
- Need for examining moderation of predictive pathways;

- Need for examining the effects of spousal support from former spouse, particularly its role as a moderator of effects of contextual socioeconomic stressors.

Hypothesized Relationships

The Family Stress Model

To model the mechanisms of influence, the present study will adopt a model of family stress and adaptation, or the "family stress model" (Conger, Rueter, & Conger, 2000; Lavee, McCubbin, & Patterson, 1985; Lempers, Clark-Lempers, & Simons, 1989). The central questions addressed by family stress investigators are related to the identification of stressors—how much and what kind; the mechanisms of influence—how are these stressors mediated by various resources such as personal, family, and community; the response of the family to these stressors; and what family processes shape the course of family adjustment and adaptation over time. Coupled with recent advances in longitudinal modeling techniques, the family stress paradigm offers an effective approach for the simultaneous modeling of psychological , intra-familial, and social variables. By doing so, the individual and collective contributions of these influences can be ascertained (McCubbin & Patterson, 1983a).

One of the earliest attempts at building a conceptual model identifying variables which account for the observed differences among families in their adaptation to stressors has been the ABCX family crisis model from Hill (1949, 1958). According to this model, the stressor event (A) interacts with the family's crisis resources (B) and the family's interpretation of the events (C), which eventually produce the crisis (X). A more recently developed model, the Double ABCX model of family stress and adaptation (McCubbin & Patterson, 1982, 1983a, 1983b), builds on Hill's (1949, 1958) ABCX model of family stress

and crisis. It redefines precrisis variables and adds postcrisis variables in an effort to describe (a) the additional life stressors and strains, prior to or following the crisis-producing event, which result in a pile-up of demands; (b) the range of outcome of family processes in response to this pile-up of stressors (maladaptation to bonadaptation); and (c) the intervening factors that shape the course of adaptation: family resources, coherence and meaning, and the related coping strategies.

Models of family stress (cf. Conger, Rueter, & Conger, 2000; Lavee, McCubbin, & Patterson, 1985; Lempers, Clark-Lempers, & Simons, 1989) have been widely used for modeling the effects of economic hardship on family relationships. According to the model, contextual socioeconomic stressors such as negative economic events (e.g., loss of a farm or business) and low income directly lead to economic pressures within the family (see Figure 1; adapted from Conger, Rueter, & Conger, 2000).

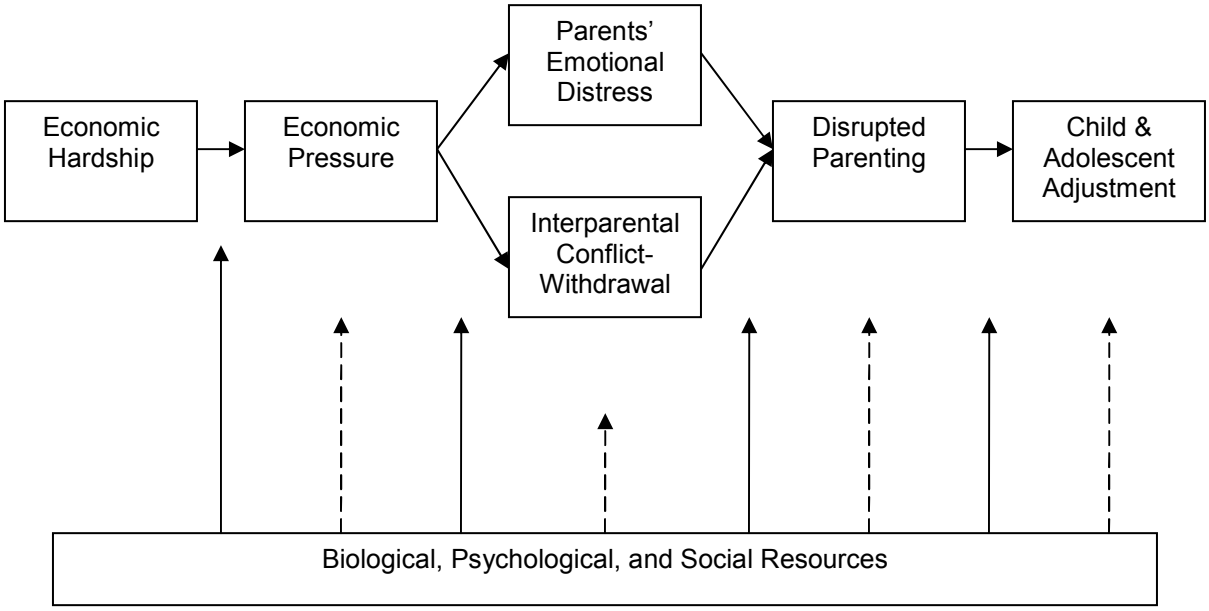


Figure 1. The family stress model

These economic stressors lead to perceived economic pressure, which includes psychologically meaningful events and conditions within the life of the family, such as the inability to purchase basic necessities such as adequate food and medical care that result from economic hardship and that impinge on the emotional health and ongoing relationships of parents. According to the model, family economic stress process involves various levels of adversity, from the family's position in the economic structure of the community (i.e., hardship itself), to the daily pressures created by hardship, to the emotional lives and social ties of parents. Children and adolescents in the family do not directly experience the risk and adversity created by the hardship; rather, by the response of the parents to the financial difficulties they face. In other words, the adversity experienced by the children is due to the hardship-related emotions and behaviors of parents. So, contextual socioeconomic stressors indirectly impact the children and adolescents through their parents.

General Theoretical Model

Figure 2 presents the overall theoretical model which illustrates the associations among contextual socioeconomic stressors, parenting, and parent and child mental health. The general theoretical model (Figure 2) is based on the family stress model as described by Conger and associates (2000; see Figure 1). As noted previously, various models of family stress (cf. Conger, Rueter, & Conger, 1994, 2000; Lavee, McCubbin, & Patterson, 1985; Lempers, Clark-Lempers, & Simons, 1989) have been widely used for modeling the effects of contextual stressors on family relationships. In accordance with the model, contextual socioeconomic stressors such as negative life events (e.g., loss of job and financial problems), economic stress, and work-related stress direct impact the emotional health and parenting effectiveness of parents, which in turn, negatively impact the mental health of their

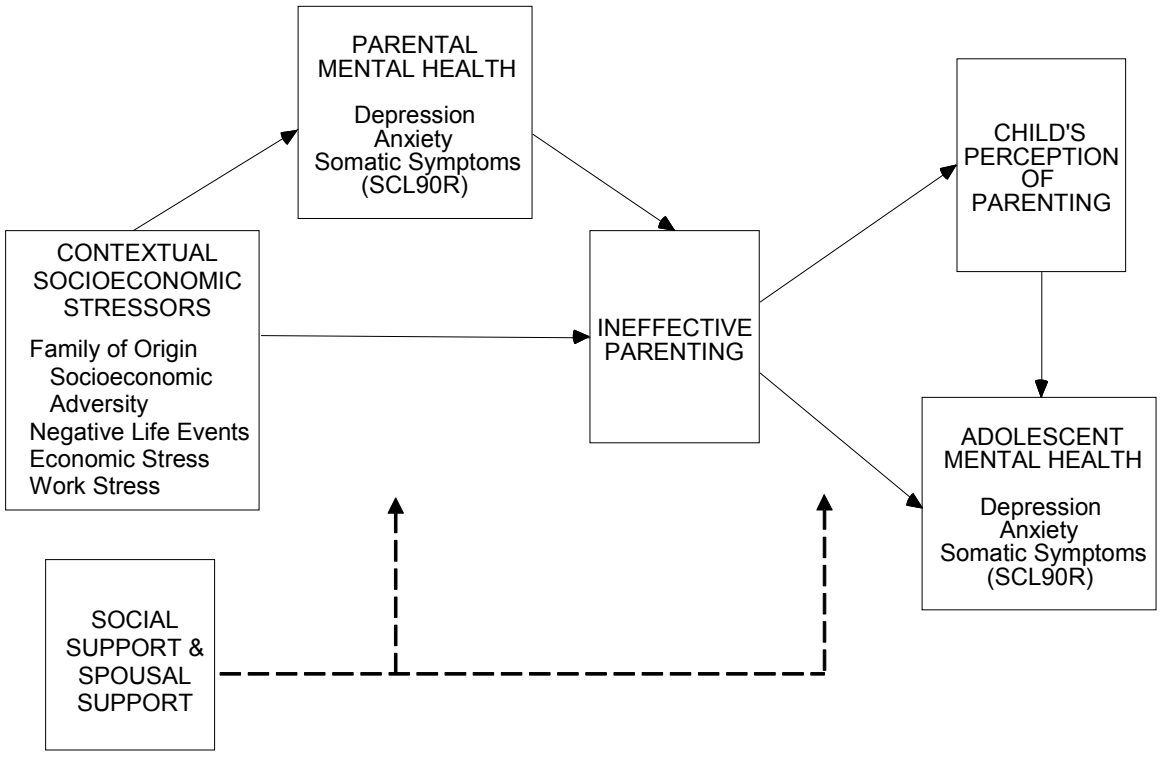


Figure 2. General theoretical model

adolescent child. According to the model, children and adolescents in the family do not directly experience the risk and adversity created by the hardship; rather, they experience the adversity through the response of the parents to the external stressors they face. In other words, the adversity experienced by the children is due to the hardship-related emotions and behaviors of parents. The net effect is the negative impact of contextual socioeconomic stressors indirectly on the children and adolescents through their parents.

As previously noted, although buffering effects are deemed important in the developmental literature on resilience and carry theoretical significance, they are still understudied and are infrequently found in the literature on resilience (Ensel & Lin, 1991; Luthar, Cicchetti, & Becker, 2000; Masten, 2001). Furthermore, existing studies using the family stress model have mostly used samples of married dual-parent families instead of

single-parent families. To address this need, the *moderation* or "buffering effect" of social resources among single-parent families (i.e., divorced single mothers) will be examined in this study. In this model, social resources such as support from ex-spouse and support from friends are expected to reduce or buffer the impact of contextual socioeconomic stressors on the single-parent mothers' mental health and parenting ineffectiveness. Social support includes not only tangible objects such as food, housing, and monetary support, but also includes emotional support as well. Spousal support in this study will be defined in terms of the support of former spouse for the sample of divorced single-parent mothers. Statistically, a buffering effect would be represented by a significant reduction in the connection between contextual variables (negative life events, economic stress, and work-related stress) and parent's mental health and parenting ineffectiveness. In turn, moderation is expected between ineffective parenting and adolescent mental health outcome. Although the model is largely consistent with the *strain* perspective, selection variables such as education level and anti-social behavior trait may be added to the model to test the *selection* hypothesis. Modeling the affects of contextual stressors on parenting quality, including education and anti-social behavior traits, Simons, Beaman, Conger, and Chao (1993), found equal support for both the strain and selection hypotheses.

Contextual Socioeconomic Stressors and Parenting

Negative life events have been found to erode positive and effective parenting skills among mothers. In a study comparing the effects of environmental risks on the parenting among drug-abusing and non drug-abusing mothers, researchers found that women with five or more risks described parenting as being more stressful and indicated greater inclination towards abusive and neglectful behavior, placing their infants at increased risk for poor

parenting, abuse and neglect (Nair, Schuler, Blacka, Kettinger, & Harrington, 2003). The maternal risk factors assessed were: maternal depression, domestic violence, non-domestic violence, family size, incarceration, no significant other in home, negative life events, psychiatric problems, homelessness, and severity of drug use. In a follow-up commentary, Kelley (2003) highlighted the importance of examining more closely the concomitant home environment in which the abusive parenting occurs. Citing several studies to support, Kelley (2003) suggested that the caregiving environment for children exposed prenatally to substances of abuse, is often far more detrimental to child outcomes than the prenatal exposure to drugs itself.

A study of the effects of environmental factors on parental stress among a sample of over 1,000 Swedish mothers also found similar results (Ostberg & Hagekull, 2000). Specifically, high workload, low social support, perception of the child as fussy-difficult, negative life events, child caretaking hassles, more children in the family, and high maternal age related directly to more stress. A surprising 48% of the variance in parenting stress was explained by their model. These results are consistent with a subsequent study with 16,000 Swedish families, where the researchers found low social support and single motherhood, among factors, to be significant predictors of parenting stress (Sepa, Frodi, & Ludvigsson, 2004).

Parent's Mental Health and Parenting Practices

Based on the family stress model (Conger & Elder, 1994), researchers have identified specific mediating paths, such as mental health, between economic hardship and the different domains of parenting (e.g., Leinonen, Solantaus, & Punamaki, 2002). In their study involving 527 Finnish mother-father-child triads, the researchers showed that economic hardship

created economic pressures for both parents (Leinonen, Solantaus, & Punamaki, 2002). Specifically, for fathers, both the general and specific pressures were further associated with symptoms of anxiety and social dysfunction, whereas for mothers, only the specific economic pressures were negatively reflected in mental health by increasing depressing mood and anxiety symptoms. Paternal anxiety was then associated with hostile marital interaction, perceived by the wife, and maternal anxiety with low marital support, perceived by the husband. The negative marital interaction finally was subsequently associated with poor parenting, especially among the fathers. Fathers' anxiety was also directly related to their punitive and noninvolved fathering, and social dysfunction to noninvolved fathering. Depressive symptoms in mothers were negatively reflected in authoritative mothering. Finally, the results revealed that supportive and non-hostile marital interaction was able to moderate the negative impact of economic hardship on parenting. The findings suggest that mothers and fathers fulfilled gender roles in dealing with the family economy and relationships. Subsequent studies have confirmed that a reduction in disposable family income constitutes a risk for child mental health through increased economic pressure and negative changes in parental mental health, marital interaction, and parenting quality (Solantaus, Leinonen, & Punamaki, 2004).

In a study examining the specificity of interpersonal relationships mediating mental health symptoms across parent-child generations, the results confirmed that parental mental-health problems can compromise a mother's and father's parenting abilities and represent a threat to their children's adjustment. Furthermore, the results suggested that the different types of parental mental-health problems initiate specific paths between parental and child mental-health problems (Leinonen, Solantaus, & Punamaki, 2003).

Baydar, Reid, and Webster-Stratton (2003) showed that mothers with mental health risk factors (i.e., depression, anger, history of abuse as a child, and substance abuse) exhibited poorer parenting along three domains of parenting (i.e., harsh/negative, supportive/positive, inconsistent/ineffective) than mothers without these risk factors. However, these at-risk mothers benefited from the parent training programs as much as mothers who were not at risk.

Evidence abounds as to the negative impact of maternal depression on children, husbands/partners, and family. Children of depressed women show deficits in social, psychological, and cognitive domains and are at increased risk for depression themselves and other psychiatric illness such as conduct disorder. They are also at an increased risk for child abuse. The mechanisms by which maternal depression may lead to child psychopathology including genetics, poor parenting, modeling, and environment are explored (Burke, 2003). Previous research has shown that a significant percentage of men become depressed when their wives/partners are depressed particularly if they have postnatal depression. Subsequently, there is an increase in marital discord and conflict within families of depressed women, all of which can have a deleterious effect on children (Burke, 2003).

In a recent study, relationships between 43 high-risk adolescents and their caregivers were examined qualitatively. Ungar (2004) found that parents and other formal and informal caregivers such as youth workers and foster parents were found to exert a large influence on the behaviors that bolster mental health among high-risk marginalized youth. He found that teenagers seek close relationships with adults in order to negotiate for powerful self-constructions as resilient. High-risk teens say they want the adults in their lives to serve as an audience in front of whom they can perform the identities they construct both inside and

outside their homes. This pattern was evident even among youth who presented as being more peer-than family-oriented (Ungar, 2004).

Parenting and Adolescent Mental Health

Several landmark studies have established that parenting affects child development in various ways (Belsky, 1984; Bowlby, 1988; Conger & Conger, 2002; Darling & Steinberg, 1993; Hetherington, 1989; Lempers, Clark-Lempers, & Simons, 1989; Maccoby & Martin, 1983; McLoyd, 1990, 1998). In particular, several studies have shown that parenting affects the child's mental health, for example, externalizing and internalizing problems in adolescents (Galambos, Barker, & Almeida, 2003), delinquency, conduct disorder, and antisocial behavior (Loeber, & Dishion, 1983; Patterson, Reid, & Dishion, 1992), and alcohol and substance use (Dishion, Patterson, & Reid, 1988). Underscoring the importance of parenting in the child's development is the fact that parenting has long-term consequences. For example, numerous studies have consistently demonstrated the intergenerational continuity of abusive or harsh parenting (Belsky, 1994; Egeland, Jacobvitz, & Papatola, 1987; Putallaz, Constanzo, Grimes, & Sherman, 1998; Simons, Whitbeck, Conger, & Wu, 1991; Straus, Gelles, & Steinmetz, 1980).

Most relevant to the present study is research demonstrating how parenting mediates the effects of extra-familial stressors, particularly economic stress, on child well-being (e.g., Barrera et al., 2002; Conger & Conger, 2002; Ge, Conger, Lorenz, & Simons, 1994; Leinonen et al., 2002; Lempers, Clark-Lempers, & Simons, 1989; Parke et al., 2004). These studies collectively highlight the fact that the parent-child relationship plays a critical role in the child's development and is a key mechanism through which extra-familial stressors affect the child.

In recent years, the parent-child relationship has been increasingly recognized as a major protective factor in the development of adolescent mental health problems, particularly substance use. Considering the critical role of parenting in the developmental trajectory of children, several parenting interventions have been developed, with the key aim of improving parenting (e.g., Hawkins, Catalano, & Miller, 1992; Molgaard, Kumpfer, & Fleming, 1987). In an effort to understand how stressful life experiences impact child/adolescent mental health, research has increasingly focused on parenting as an important protective factor in reducing adolescent mental health and behavioral problems. For example, Grant and colleagues (2003) conducted a meta-analysis with 46 studies and found support for a model in which negative parenting (e.g., hostility, lack of support) mediated the relation between poverty and child and adolescent internalizing and externalizing behaviors. The findings from the evaluation of prevention programs complement the resilience research. In a recent meta-analysis of 1,200 outcome studies of prevention programs in the United States, (Durlak, 1998) demonstrated that the same set of risk factors at the levels of the individual child, the family, the peer group, the school environment, and the broader community is associated with eight major negative outcomes. These include problems such as child behavioral problems, mental health problems, school failure, drug use, and child abuse. Also, the same set of protective factors, including the availability of social support, and connectedness to school and family, is associated with positive outcomes. In the review, studies consistently showed that punitive parenting behaviors were risk factors both for externalizing behavior problems and drug use. In contrast, positive parenting behaviors were identified as protective factors for externalizing behavior problems and drug use (Durlak, 1998).

Perception of Parenting and Adolescent Mental Health

One of the central components of the original ABCX Model of family stress (Hill, 1949, 1958) is the family's definition or perception of the stressor (the "C" component of the ABCX Model). The "C" factor is the subjective assessment the family makes of the seriousness of the stressor and the individual family member's personal experience of the stressor. The Double ABCX Model extends Hill's by including the critical psychological, intra-familial, and social resources families use over time. Most pertinent to the present study is the adolescent child's perception of the single-parent mother's parenting practices. In terms of the Double ABCX paradigm, changes in the single-parent mother's parenting practices and the child's perception of his/her mother's parenting represent the post-crisis stage, where intra-familial processes, especially parent-child relations, change over time as a result of prior stressors (Pearlin & Schooler, 1978).

Having established the critical link between parenting and child outcomes, one aspect of this mechanism that has been understudied is the role of a child's perceptions of parenting. Previous studies have demonstrated that the adolescent's perception of their parents' parenting style is a stronger predictor of adolescent behavioral outcomes than the parents' own perception of their parenting (cf., Cohen & Rice, 1996). Logically, it makes sense that the child's perceptions of parenting behavior is the mediating mechanism linking actual parenting behaviors and the child's response to those behaviors. The child must first perceive the parenting behavior, either through observations of expressions of parenting behaviors toward the child or someone else or through direct experience of parenting behaviors (e.g., a spanking). Once the child has perceived the parenting behavior, then he/she will respond to it consistent with the manner in which it was perceived. In this sense, assessing the child's

perception of parenting is critical, given the fact that many studies have shown that the parents' self-report of their own parenting behaviors tend to differ significantly from the way children perceive it (e.g., Gaylord, Kitzmann, & Coleman, 2003). One study examining the link between perceived parenting behaviors and generalized anxiety disorder (GAD) revealed that adolescent perceptions of parental alienation and rejection were strongly associated with adolescent GAD symptom scores (Hale, Engels, & Meeus, 2006). Furthermore, mid-adolescent females perceived more parental alienation in relation to their GAD symptom scores than both early and mid-adolescent males. Also, early adolescent males perceived more parental rejection in relation to their GAD symptom scores than mid-adolescent males (Hale, Engels, & Meeus, 2006). The present study seeks to address the need for further research in this area by including a measure of child's perception of parenting in the model. It is expected that the child's perception of parenting will significantly mediate the path from actual parenting behaviors to child's mental health outcome.

Direct, Indirect, and Moderating Effects of Spousal Support on Mental Health and Parenting

Studies have found supportive spousal relationships to be moderators of stressors. For example, Noor (2002) found that spousal support moderated the relationship between work variables (i.e., long work hours, autonomy, tedium and overload) and conflict. This is consistent with an earlier study examining the moderating effect of spousal support on the negative impact of parental overload on family-work conflict (Aryee, Luk, Leung, & Lo, 1999). In a recent study investigating the impact of poverty and economic pressure upon the adjustment of mothers and children in immigrant Latino families, researchers found that maternal depression mediated the relationship between maternal economic pressure and child adjustment (Dennis, Parke, Coltrane, Blacher, & Borthwick-Duffy, 2003). Furthermore,

social support was found to further moderate the relationship between maternal depression and child internalizing problems.

The direct and indirect effects of the marital subsystem on the functioning of the family system have been well-documented (see Parke, 2004 for review). Marriage has been linked to both direct positive effects as well as buffering effects of stressors on family relationships. Many studies comparing samples of married and non-married couples have demonstrated that those who are married persons often show more positive results in various measures of happiness and well-being, including global happiness (Glenn & Weaver, 1988; Lee, Seccombe, & Shehan, 1991; Ruvolo, 1998; Stack & Eshleman, 1998) and life satisfaction and related indicators of psychological well-being (Gove, 1972; Gove, Hughes, & Style, 1983; Gove, Style, & Hughes, 1990; Marks, 1996; Marks & Lambert, 1998; Mastekaasa, 1992, 1993, 1994; Ross, 1995). In their review of relevant literature, Lamb, Lee, and DeMaris (2003) noted that married individuals also seem to fare better in terms of health measures, such as physical health (Waite, 1995); and life expectancy (Lillard & Waite, 1995; Murray, 2000). Most relevant to the present study, research has consistently shown that married persons have more positive mental health and non-married. For example, studies have shown that married individuals tend to be less depressed than the never-married (Horwitz, White, & Howell-White, 1996; Marks, 1996; Marks & Lambert, 1998; Ross, 1995). The implication of these findings for single-parent mothers is that they are at-risk for being adversely affected by environmental stressors due to both a loss of a significant support structure and the negative events associated with the divorce process itself. Thus, it is the goal of this present study to investigate modifiable risk and protective factors that may buffer the negative effects of stressors in the lives of single-parent mothers.

In addition to buffering the effects of stressors on parenting behavior, the marital relationship also buffers the effects of stressors on the mental health of individuals as well. One consistent theme in the literature is that social support in the form of marital support acts as a buffer to stress and its destructive consequences. It can help prevent stress by making harmful experiences seem less consequential or provide valuable resources for coping when stress does occur (Sarason, Sarason & Pierce, 1990). There is also ample evidence to support the buffering effect of family support on the effects of health-related stressors. Roberts, Cox, Shannon and Wells (1994) found that spousal support had some buffering effect for breast cancer patients. In his review of relevant literature, Schwarzer (2003) noted that social support plays a role in the coping with various health conditions, such as myocardial infarction and cancer, and in the recovery phase (Revenson, 1994; Schwarzer, Knoll, & Rieckmann, in press; Wills & Filer-Fegan, 2001; Schwarzer, 2003). Availability of social support in the form of marital support is also associated with a reduced risk of mental illness and physical illness, and even mortality (Cohen, 1988; Cohen & Wills, 1985; House, Landis, & Umberson, 1988; Schwarzer & Leppin, 1989; Schwarzer, 2003).

Although gender differences in the effects of partner support are not hypothesized in this study, studies have noted how women and men may differ in their social networks. Specifically, it has been suggested that women tend to rely more on contextual relationships (i.e., extended family and friends) and therefore have a larger social network that is more intimate and offers support in multiple forms and from multiple sources. Men, on the other hand, often rely solely on their spouses as the support provider (Glynn, Christenfeld, & Gerin, 1999; Greenglass, 1982; Hobfoll, 1986, 1998; Klauer & Winkeler, 2002; Knoll & Schwarzer, 2002; Schwarzer, 2003). In this consideration, women are more likely to be well

integrated socially and have structures readily available that will buffer the effects of environmental stressors even if their husbands appear to be unsupportive. This study includes both social support and support from spouse in the same model. The results of this study will also demonstrate whether spousal support remains to be a significant predictor of the mother's mental health and parenting, even while including social support as a predictor variable. It is possible that while a larger social network is characteristic of women, more so than men, spousal support still remains to be an equally strong and significant source of support for women.

Using a similar sample as that of the present study, Lorenz, Conger, Montague, and Wickrama (1993) compared farming and non-farming husbands' and wives' depressive symptoms by including spouse support as both a mediating and a moderating variable. Using three waves of data from the Iowa Youth and Families Project, the results showed few differences between farmers and non-farmers, but the relation between economic pressure and distress operates differently for husbands and wives. For husbands, wives' support buffers the relation between economic pressure and husbands' sense of control over events in their lives, which in turn reduces depression. For wives, husbands' support both directly reduces their depression and buffers the effects of economic pressure on depression by weakening the relation between sense of control and feelings of depression (Lorenz et al.,1993). This study confirmed the findings of an earlier finding that the level of spouse support was positively related to supportive parenting; that is, spousal support moderated the impact of economic strain on supportive parenting; however, it was only true for mothers and not fathers (Simons, Lorenz, Conger, & Wu, 1992). In conclusion, the researchers suggested

the need for further study in the moderating effects of spousal support and support from immediate family members on the experience of environmental pressure in such families.

Single Parent Mothers' Relationship to Former Spouse and the Co-parenting Relationship

More often than not, children end up in the custody of the mother after divorce. It is estimated that more than 85 percent of children whose parents are divorced are in the custody of their mothers (Furstenberg & Cherlin, 1991). Considering the high prevalence of post-divorce children living with their mothers, this underscores the need for special attention to be given to the unique experiences of post-divorce, single-parent motherhood. As noted previously, single-parent mothers experience a unique set of challenges. Often, single-parent motherhood is concomitant with poverty, poor parenting, and several other health-related risk factors. However, a divorce or separation does not necessarily preclude the chance for post-divorce children from experiencing positive, warmth, and effective parenting from their divorced parents. Theoretical models have been proposed to account for the phenomenon of post-divorce parenting (e.g., Abidin, 1992; Abidin & Brunner, 1995). In such research, many different terms have been used to describe post-divorce parenting arrangements. Terms such as *coparenting, shared parenting, parenting alliance* and *parenting partnerships* refer to the involvement of both parents in childrearing after divorce and encompass a range of cooperative efforts between parents. Shared or joint custody refers to legal arrangements and may or may not be used synonymously with the above terms. Shared parenting does not necessarily involve a fully equal division of childrearing responsibility and caretaking, and mothers continue to be the primary resident parent even when joint legal custody is designated (Seltzer & Bianchi, 1988). Thus, the difference between "coparenting" and couple or marital relationship is the concept of a shared parenting role. That is, regardless of marital

status or cohabitation, individuals may work together in their roles as parents. In fact, research indicates that the coparenting relationship is more powerfully and proximally related to parenting than other aspects of the couple relationship. When the general couple relationship and coparenting are compared in the same study, coparenting often is found to be of greater significance. For example, for married couples, Abidin and Brunner (1995) found that the *parenting alliance, not marital adjustment,* is significantly associated with parenting style. Bearss and Eyberg (1998) reported that the parenting alliance had a stronger relationship with child problems than did marital adjustment. More recently, Feinberg, Neiderhiser, Reiss, Hetherington, and Simmens (2000) confirmed the findings of these studies in their analysis of data from nondivorced couple sample. Similar findings have been obtained for divorced parents as well (see Whiteside & Becker, 2000 for review; see also Camara & Resnick, 1989; Ihinger-Tallman, Pasley, & Beuhler, 1995; Feinberg, 2002).

Most research examining the moderating effects of spousal support has been conducted with married couples. Many studies have examined the negative effect of divorce and poor marital quality on families and children. However, fewer studies have examined the marital relationship among post-divorce couples as a moderator of environmental stressors. In other words, fewer studies have explored the possibility of divorced and separated parents demonstrating positive and effective parenting skills and the mechanisms through which those skills may develop and may be strengthened. Additionally, previous studies have shown that single parent families face a unique set of struggles. Often neighborhood poverty, economic stress, and poor family environment are concomitant with single parenthood. Thus, the purpose of the first study is to specifically examine single parent mothers and explore the

moderating effects of support of former spouses on their parenting practices and mental health.

Hence, the present study extends previous research adopting the family stress model by using a sample of divorced single-parent mothers as well as a sample of two-parent families from rural Midwestern communities affected by the 1980s farm crisis. Specifically, this study expands previous studies by simultaneously examining the influence of contextual socioeconomic as well as mental health factors on parenting practices, and also the direct, indirect, and moderating effects of spousal support among divorced single-parent mothers.

Summary of Hypothesized Paths

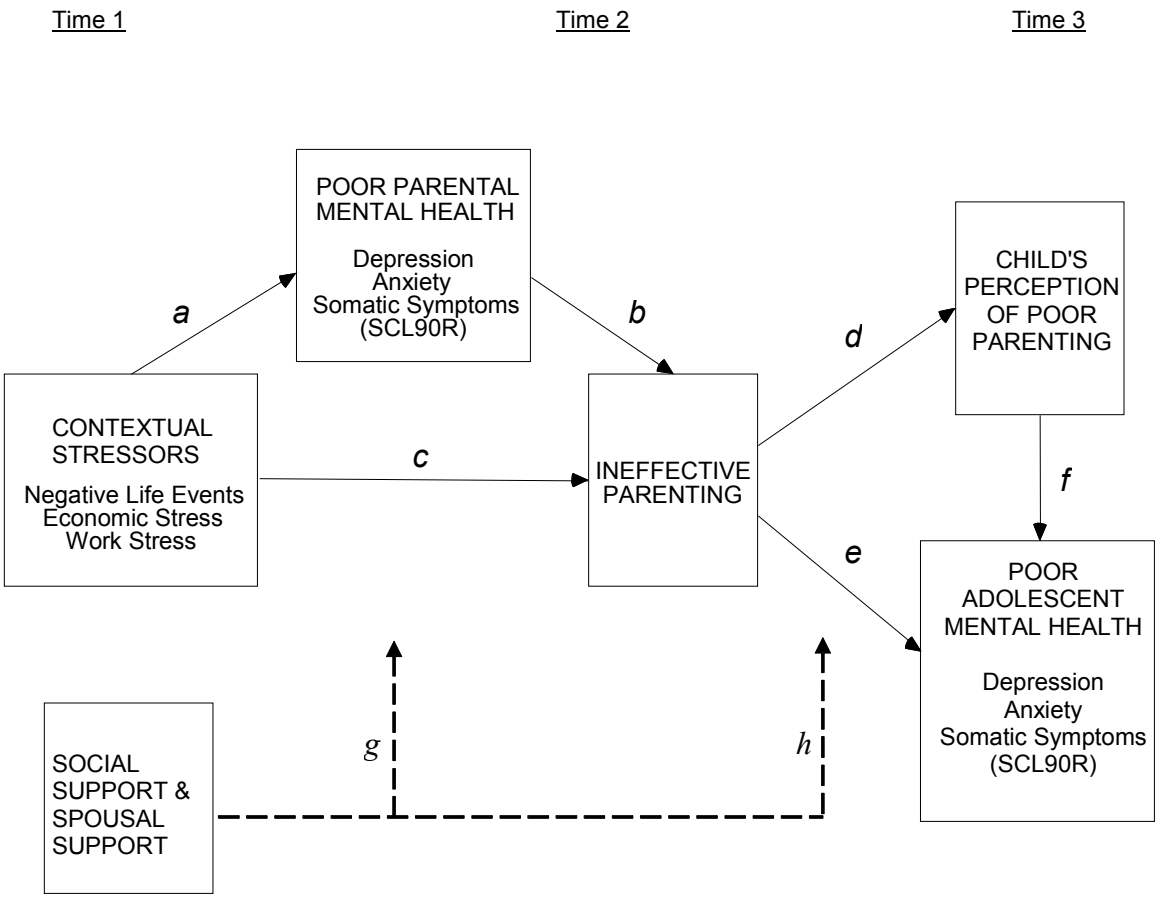


Figure 3. Summary of hypothesized structural paths.

Hypothesis #1 (path a)

Each contextual stressor (negative life events, economic stress, & work stress) at Time 1 variables are expected to significantly predict poor parental mental health at Time 2 ($\beta_a > 0$).

Hypothesis #2 (path b)

Poor mental health at Time 2 is expected to significantly predict ineffective parenting ($\beta_b > 0$) at Time 2.

Hypothesis #3 (path c)

Each contextual stressor (negative life events, economic stress, & work stress) at Time 1 is expected to directly predict ineffective parenting at Time 2 prior to adding mental health of parent into the model ($\beta_c > 0$) at Time 2. However, this direct effect is expected to diminish significantly after adding mental health of parent into the model, which would suggest that the contextual effects have an indirect on the ineffective parenting of parents and ($\beta_c = 0$). In other words, the effects of contextual socioeconomic stressors on parenting are mediated through the parent's mental health.

Hypothesis #4 (path d)

Ineffective parenting at Time 2 is expected to significantly predict the adolescent's perception of poor parenting practices ($\beta_d > 0$) at Time 3.

Hypothesis #5 (path e)

Ineffective parenting at Time 2 is expected to directly predict the adolescent child's mental health ($\beta_e > 0$) at Time 3 prior to adding the child's perception of poor parenting practices as a mediating variable. However, the direct effect is expected to diminish significantly after adding the child's perception as the mediating variable, which would

suggest that ineffective parenting has a significant indirect effect on the child's mental health ($\beta_e = 0$).

Hypothesis #6 (path f)

Adolescent's perception of parenting practices at Time 3 is expected to significantly predict the adolescent's mental health at Time 3 ($\beta_f = 0$).

Hypothesis #7 (path g)

Social support and spousal support are expected to buffer the effects of the contextual socioeconomic stressors at Time 1 on the parent's mental health and parenting behaviors at Time 2. Using multiple group analysis in SEM, we expect to see a chi-square difference value for each path of greater than 3.84 ($\chi^2 > 3.84$).

Hypothesis #8 (path h)

Social support and spousal support are expected to buffer the effects of ineffective parenting at Time 2 on the child's perception of parenting and the child's mental health at Time 3. Using a stacked model approach in SEM, we expect to see a chi-square difference value for each path of greater than 3.84 ($\chi^2 > 3.84$).

It is expected that hypothesized relationships exist for both single and married mothers. Although there may be overall mean level differences in study variables (parental mental health, parenting, adolescent mental health) between the two groups, it is expected that the mechanisms of influence of the contextual socioeconomic factors on mental health and parenting will be the same.

CHAPTER 3: METHODOLOGICAL ISSUES AND ANALYTICAL STRATEGIES

Methodological Issues

Missing Data

Missing data are almost always a problem in longitudinal research, and may be true for the samples used in this study as well. Being a multi-wave panel study, the Iowa Single Parent Project sample used in this study also contains missing data. One unique problem of these particular samples is that families facing economic difficulties may move out of the area in search for employment, resulting in subject non-response and thus contributing to the missing data problem. Item non-response, differential attrition, failure to obtain measurements at equal time intervals, and unbalanced panel designs are difficult to analyze and remain a threat to the validity of a study. There are three basic mechanisms that produce missing data:

(1) *Missing completely at random (MCAR)* – This is missingness by pure chance. In technical terms, data is called missing completely at random if the probability of a missing response is independent of all the measure and unmeasured characteristics of the individuals under study;

(2) *Missing at random (MAR)* – Unlike MCAR, data is called missing at random if missingness does not depend on the missing values, but may depend on other observed characteristics of the individuals. For example, income may be the variable of interest, but often depends on the individual's education level. So, if less educated people tend to not report their income, then the missing income values are MAR because missingness depends in part on education level;

(3) *Missing not at random (MNAR)* – This is also called, "non-ignorable" (NI) missingness. This is the most problematic type of missingness. This is when missingness is related to the value that would have been observed. For example, if the reporting of income depends on the income level itself.

When examining a dataset, there is no way to distinguish between the MAR and MNAR cases (Sinharay, Stern, & Russell, 2001). However, there are satisfactory techniques for analyzing MAR data with traditional statistical models, but additional modeling is needed for analyzing MNAR data.

For family studies, Acock (2005) suggests that MAR instead of MCAR is a more reasonable assumption. One exception, however, is when data are *missing by design* (Acock, 2005). For example, experimental fatigue when collecting data from young children may lead to as much as 80% of the values missing. In this case, using listwise or casewise deletion would not make sense because it would leave the researcher with very little data to work with. These data, however, would meet the requirements for MCAR because the random process would insure that missingness is unrelated to the child's score on any of the questionnaire items (Acock, 2005).

As noted previously, the missing data for a variable are MAR if the likelihood of missing data on the variable is not related to the participant's score on the variable, after controlling for other variables in the study. These other variables provide the *mechanism* for explaining missing values. In other words, a variable is a mechanism if it helps to explain whether or not a respondent answers a question (Acock, 2005; Raghunathan, 2004; Schafer, 1997). Common mechanisms include education, race, age, gender, and indication of psychological well-being (Acock, 2005).

Following Acock (2005), the missing data for the present study will be assumed MAR. FIML assumes MAR and is appropriate for analyses with such a sample. Hence, for the present study, FIML will be used for the structural equations modeling, as offered in software programs, Mplus and AMOS, for handling missing data. See Appendix 7 for a full discussion of approaches to handling missing data.

Power Analysis and Sample Size Determination in SEM

Research studies requiring often-marginalized groups of individuals or relating to stigma-laden issues (e.g., AIDS) are often limited in terms of sample sizes, presenting challenges to study design and analysis. In the present study, the sample of divorced mothers has been determined to be sufficiently large (N=207) for the structural equation models used in this study, following the guidelines suggested by MacCallum, Browne, and Sugawara (1996) and Kim (2005). See Appendices 5 and 8 for full details on sample size determination and power analysis. Where possible, models with a large number of parameters were reduced to smaller models by using limiting the number of latent factors estimated. For example, first-order growth models will be created by using index scores of indicator variables instead of using second-order growth models. Also, when testing for moderating using multiple group analysis, smaller nested models will be used when testing each path, instead of using the full model.

Non-Normality of Data

Non-normality of data is expected with the variables in the present study. Some of the variables (e.g., family income) may lack normality and need transformation. Also, multiple imputation (MI) and maximum likelihood (ML) analytical approaches usually assume a multivariate normal distribution for the variables. Likewise, most latent variable models are

based on the assumption that the observed variables are continuous with a multivariate normal distribution. The problem is that in most studies, such as the present study, normally-distributed variables are rare. Often, due to the nature of the problem or the design of the questionnaires, observed variables are in non-normal form such as ordered categorical variables, especially in the social and behavioral sciences (Eickhoff & Amemiya, 2005). In social and behavioral research, data are frequently collected based on Likert scales (e.g., "disagree," "neutral," "agree"), which are actually polytomous data, specifically ordered categorical responses, as is the case with the variables used in the present study. Because the problems that often plague longitudinal also present a threat to the present study, the problem of non-normality of data must be addressed.

To address problems of non-normality, traditional approaches have included transformations of the observed data (see Table 1). In many instances, however, the choice of a transformation to improve the approximation to normality is not obvious. For such cases it is better to let the data suggest a transformation. To do this, a family of transformations called, *power transformations* or "Box-Cox transformation," is the preferred approach (Box & Cox, 1964). While the Box-Cox transformation does not guarantee normality, it is perhaps the best method available. Nonetheless, any transformations should be carefully checked for possible violations of the tentative assumptions of normality. Box and Cox (1964) considered the slightly modified family of power transformations:

$$x^{(\lambda)} = \begin{cases} \dfrac{x^{\lambda} - 1}{\lambda} & \lambda \neq 0 \\ \ln x & \lambda = 0 \end{cases}$$

Table 1

Common Transformations

Transformation	Original Observed Data
Square root $\sqrt{X}$	Counts or moderate positive skew
Logit $\log it(\hat{p}) = \frac{1}{2}\log\left(\frac{\hat{p}}{1-\hat{p}}\right)$	Proportions
Fisher's Z $z(r) = \frac{1}{2}\log\left(\frac{1+r}{1-r}\right)$	Correlations r
$Log_{10}(X)$	Positive skew (substantial)
$Log_{10}(X+C)$	Positive skew (with zero)
1/X	Positive skew (severe)
1/(X+C)	L-shaped (with zero)

which is continuous in λ for x > 0. Given the observations $x_1, x_2, \ldots, x_n$, the Box-Cox solution for the choice of an appropriate power λ is the one which maximizes the expression

$$\ell(\lambda) = -\frac{n}{2}\ln\left[\frac{1}{n}\sum_{j=1}^{n}(x_j^{(\lambda)} - \overline{x^{(\lambda)}})^2\right] + (\lambda - 1)\sum_{j=1}^{n}\ln x_j$$

is the logarithm of a normal likelihood function, after maximizing it with respect to the population mean and variance parameters, where $x_j^{(\lambda)}$ is the modified family of power transformation as defined above and

$$\overline{x^{(\lambda)}} = \frac{1}{n}\sum_{j=1}^{n}x_j^{(\lambda)} = \frac{1}{n}\sum_{j=1}^{n}\left(\frac{x_j^{(\lambda)} - 1}{\lambda}\right)$$

is the arithmetic mean of the transformed observations. When either λ=0 (logarithm) or λ=1/2 (square root) is near $\hat{\lambda}$, one of these may be preferred because of its simplicity (Johnson & Wichern, 1992).

Other approaches have included recoding responses into categories or creating index scores. For example, to address the skewed nature of the data and to reduce the importance of drinking relative to the other measures of antisocial behavior, Lorenz and colleagues (1997) constructed an antisocial index by giving respondents a score of 0 if they reported no problems or if they only reported delinquent acts before age 15, a score of 1 if they reported either one or more deviant behaviors or one or more drinking problems in the past 12 months, a score of 2 if they reported both deviant behavior and drinking problems, a score of 3 if one or more delinquent behaviors from their youth was combined with either deviant behavior or drinking problems as adults, and a score of 4 if they acknowledged all three. Similarly, low-frequency measures such as negative life events can be summed into an index score (Lorenz et al., 1997).

To assess model fit with non-normal data, a commonly-used approach is to calculate the Satorra-Bentler chi-square. However, the Satorra-Bentler chi-square is defined for continuous variables, not categorical ones. When using categorical outcome variables, it has been suggested that the best estimator to use is the weighted least squares estimator with adjusted means and variances (WLSMV; see Muthén, du Toit, & Spisic, 1997). This is the default estimator for categorical dependent variables in Mplus. The reason for this is because most social research measurements are based on the Likert-type scale, which is actually polytomous data, i.e., ordered categorical responses, rather than continuous responses. The issue for the analyst, then, is not to determine whether variables are continuous or

categorical; rather, it is to assess whether the underlying distribution assumption holds or not. Currently, popular software such as LISREL (PRELIS) and Mplus offer Mardia's test of multivariate normality. SPSS does not offer such test. Based on functions of skewness and kurtosis, it is suggested that Mardia's PK of less than 3 means that it is safe to assume that the assumption of multivariate normality is met. In Mplus, the advantage of the WLSMV method is a *generalized* method, so it is not restricted by a particular distribution assumption. Hence, it is flexible enough to accommodate non-normality of data.

Because latent variable models are based on the assumptions that the observed variables are continuous with a multivariate distribution, the reality of non-normal and polytomous variables in most longitudinal studies pose a serious threat to these assumptions. With such data, direct maximum likelihood estimation becomes computationally difficult in models involving higher dimensional latent variables since it requires maximization over multiple integrals. To address this problem, multi-stage estimation procedure which uses partitioning and weighted least squares (WLS) estimation has been developed (Christofferson, 1975; Muthén, 1978). The first partitioning involves partitioning the multivariate model into bivariate integrals. Then the thresholds and polychoric correlations in these bivariate sub-models are estimated. This reduces the computation burden by reducing the integration to only the evaluation of bivariate integrals. In the final step, the parameters are estimated by minimizing a weighted least squares (WLS) function where the weight matrix is the estimated asymptotic covariance matrix of the polychoric correlations. Fortunately, this underlying variable approach with multi-stage WLS estimation procedures has been widely implemented in popular SEM software packages, such as LISREL

(Jöreskog, & Sörbom, 1996), EQS (Bentler, 1995), LISCOMP (Muthén, 1987), and Mplus (Muthén, & Muthén, 2004).

Sample Attrition

Intimately related to the previous methodological issue of missing data is sample attrition. Sample attrition is a common problem for multi-wave longitudinal studies. Being multi-wave longitudinal panel studies, the present study samples also show considerable attrition over the study period (See chapters 5 and 8 for attrition analyses). While longitudinal data can have considerable advantages over much more widely used cross-sectional data, the collection and analysis of longitudinal data, however, may be difficult and time consuming.

Sample attrition poses a threat to validity. External validity is threatened when attrition processes systematically exclude certain segments of the population to which one wishes to generalize the results, limiting how broadly the findings may apply. The threat of attrition to the external validity can be assessed by testing for significant differences between respondents and non-respondents. In a randomized-controlled experimental design, attrition also threatens internal validity when the loss of subjects from research groups occurs in a systematic way so that those who remain in the research may be more (or less) likely to show change regardless of the effects of the intervention being studied. For example, if only those least likely to show effects remain in the treatment group, there will be fewer differences from the control group and the impact of the program will be underestimated.

Another problem is that sample attrition contributes greatly to the cost of the study is sample attrition. This is due to the fact that initial sample size estimates must take into consideration attrition and must compensate with a larger sample, incurring costs for

recruiting study participants and tracking attriters. In addition, sample attrition poses significant difficulties in terms of data analysis and renders the interpretation of estimates problematic. Such attrition may be particularly severe in areas where there is considerable mobility because of migration between rural and urban areas, where majority of the subjects in the present study resides. Many analysts share the intuition that attrition is likely to be selective on characteristics such as schooling and that high attrition is likely to bias estimates made from longitudinal data.

The concern is that those dropped out of the study ("attriters") are fundamentally different than those who chose to stay in the study. Hence, critics argue, the end result is a biased estimate made from longitudinal data. To address concerns about respondent attrition and the competing argument that the attriters are fundamentally different than the remaining sample, group differences can be assessed on the variables of interest. Variables of interest are usually background variables, such as income, marital status, gender, and education.

To assess statistical significance, chi-square (χ^2) tests and *t*-tests can be used to compare attriters to those remaining in the study on the variables of interest. For example, in a study using a sample of divorced mothers with adolescent children, Lorenz and colleagues (1997) compared attriters to those remaining in the study in their levels of antisocial behavior, negative life events, depressive symptoms, and income, among other variables. They found one important difference: Women who were excluded from the study (attriters) had an average per capita household income of $4,900, compared to with $8,400 among those who remained in the study. Reports from the field staff suggested that families who left the study were those who moved away to new jobs or to seek employment, thus explaining the lower average income among the attriters (Lorenz et al., 1997).

Overview of Analytic Strategies

The following research strategies collectively address several of the noted limitations identified in earlier research. The use of a longitudinal design, in particular, addresses several key weaknesses of past studies. First, it uses prospective information, which overcomes the possible biases of retrospective data. Second, by using two separate samples, direct comparisons can be made in the family mechanisms affecting mental health in divorced single-parent families with those in families with married parents. As noted in the literature review, longitudinal studies examining the supportive relationship between the single-parent mother and her former spouse are rare. Third, the study includes both self-report and observation report in assessing the family relationships. The use of observational rating is a particular advantage when assessing a contemporaneous reciprocal process, as is the case between the parent and child in this study. Observers can assess the reciprocity between family members and offer a third-person perspective, which is largely absent with self-report-only measures. Previous studies have noted that this measurement strategy might be more effective than participant reports in revealing the developmental processes of interest because self-report measures have been relatively insensitive to tests of intergenerational hypotheses, especially regarding romantic relationships (Conger, Cui, Bryant, & Elder, 2000).

Finally, the present study capitalizes on the recent advances in longitudinal research methodology. With the availability of several new latent variable modeling techniques, it is now possible to assess several aspects of family relationship processes in greater detail. Advantages of SEM compared to traditional approaches such as repeated measures MANOVA and multiple regression include more flexible assumptions (particularly allowing

interpretation even in the face of multicollinearity), use of confirmatory factor analysis (CFA) to reduce measurement error by having multiple indicators per latent variable, the ability of testing models overall rather than coefficients individually, the ability to test models with multiple dependent variables, the ability to model mediating variables, the ability to model error terms, the ability to test coefficients across multiple between-subjects groups, and ability to handle difficult data (time series with auto-correlated error, non-normal data, missing data, nested data).

Review of Analytic Strategies

Strategy 1: Use Path analysis to model direct effects of contextual socioeconomic stressors on adolescent mental health

Strategy 2: Modeling the mediating role of parent's mental health and parenting practices on the effect of contextual socioeconomic stressors on adolescent mental health

Strategy 3: Using multiple group analysis in SEM to test whether positive social support and spousal support moderate the effects of these contextual socioeconomic stressors on parent's and child's mental health and parenting practices

Strategy 4: Modeling the causal order between parents' mental health and parenting practices using growth curve, auto-regressive and cross-lagged modeling

Strategy 5: Using latent growth curves (LGC) model and latent class growth analysis (LCGA) to model the dynamic association between parenting practices and adolescent mental health over time

To test for group differences between the divorced and married samples, Strategies 1, 2, and 3 will use multiple group analyses for the hypothesized models, as described below, starting with the overall measurement model, and then comparing the causal links for the subsequent hypothesized models. Specifically, initial analyses will compare the results of the overall structural model, linking contextual socioeconomic stressors to adolescent mental health for both divorced and married samples. Then, in the models testing direct effects, mediation and moderation, it is expected that spousal support and social support will significantly buffer the negative effects of contextual socioeconomic stressors for both the divorced and married samples.

By strategically using a combination of latent variable modeling techniques, several aspects of family relationships will be examined: Individual developmental trajectories, etiology of adolescent mental health, mechanisms of mediation and moderation, reciprocity, and causal links. Strategies 4 and 5, in particular, will use advanced latent structural equation modeling techniques to more closely examine the relationship between mental health and parenting. Each strategy is described as follows.

Strategy 1: Use Path analysis to model direct effects of contextual socioeconomic stressors on adolescent mental health

This study is particularly interested in the long-term effects of contextual socioeconomic stressors on adolescent mental health. Given three waves of data, one approach is to simply model the direct effect of each of the contextual socioeconomic stressors (negative life events, economic stress, and work-related stress) at Time 1 on adolescent mental health at Time 3 as follows:

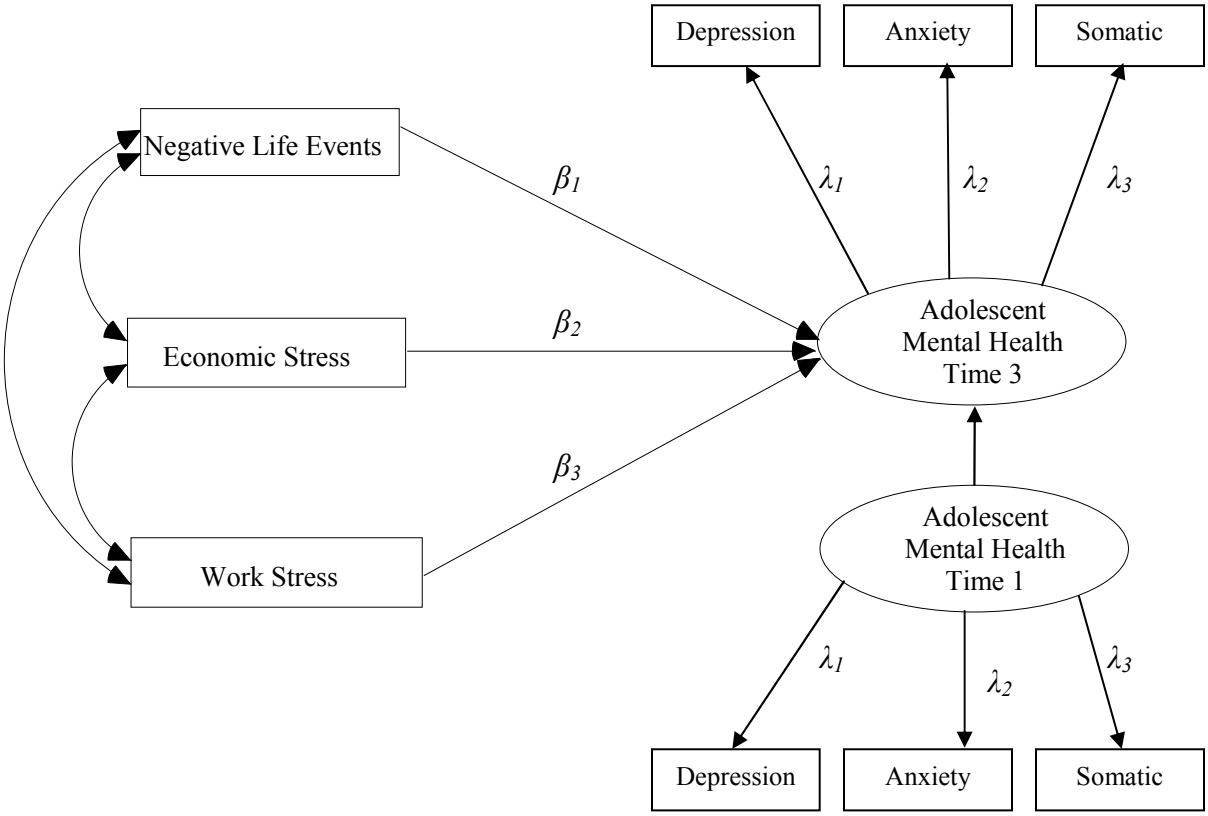


Figure 4. Test of direct effect of contextual socioeconomic stressors on adolescent mental health.

A simple path model can be specified using AMOS (Arbuckle, 2003) to test the hypothesis. It is expected that contextual socioeconomic stressors at Time 1 will significantly predict change in adolescent mental health at Time 3 (controlling for Time 1 adolescent mental health), as evidenced by a significantly positive path coefficients (β_1, β_2, β_3). The factor loadings for the adolescent mental health construct will be constrained to equality for Time 1 and Time 3 measurements. The residual terms for the adolescent mental health indicators will be correlated to account for measurement method factor.

Strategy 2: Modeling the mediating role of parent's mental health and parenting practices on the effect of contextual socioeconomic stressors on adolescent mental health

Several mediating mechanisms are proposed by the hypothesized theoretical model (Figure 3). Specifically, parental mental health and parenting practices are expected to mediate the effects of the contextual socioeconomic stressors (Hypothesis 3). Furthermore, the child's perception of parenting is expected to mediate the effect of parenting practices on the child's mental health (Hypothesis 5). Mediation is said to occur when the causal effect of an independent variable (X) on a dependent variable (Y) is transmitted by a mediator (M). "Indirect effects" estimate the magnitude of mediation. In other words, X affects Y because X affects M, and M, in turn, affects Y:

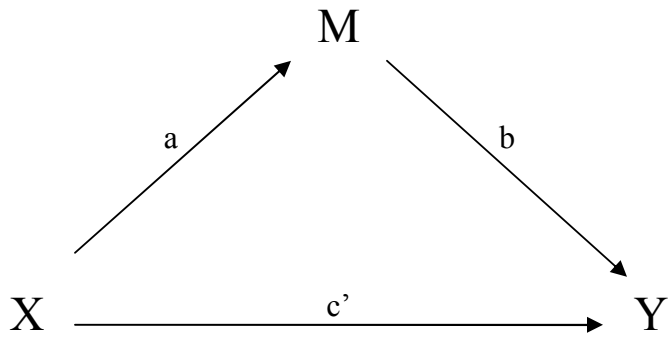


Figure 5. Basic mediational structure.

The use of mediation modeling in research studies became widespread after its conceptualization by Judd and Kenny (1981) and Baron and Kenny (1986). However, this initial conceptualization has received much criticism and has subsequently undergone revisions. Wheaton (1985) describes how moderation and mediation models are often misinterpreted and what they mean in terms of stress buffering. One word of caution noted by Wheaton (1985) that is particularly applicable to the present analyses is that an indirect effect (e.g., through social support) may actually function as a *suppressor* variable, which cannot be accounted for by the Baron and Kenny (1986) model. To summarize, Kenny,

Kashy, and Bolger (1998) outline four steps for establishing mediation, as initially described by Judd and Kenny (1981) and Baron and Kenny (1986):

(1) Step 1. Show that the initial variable is correlated with the outcome. Use *Y* as the criterion variable in a regression equation and *X* as a predictor and estimate and test path *c* which is the direct path from *X* to *Y* (without *M*). This step establishes that there is an effect that may be mediated.

(2) Step 2. Show that the initial variable is correlated with the mediator. Use *M* as the criterion variable in the regression equation and *X* as a predictor and estimate and test path *a*. This step essentially involves treating the mediator as if it were an outcome variable.

(3) Step 3. Show that the mediator affects the outcome variable. Use *Y* as the criterion variable in a regression equation and *X* and *M* as predictors and then estimate and test path *b*. It is not sufficient just to correlate the mediator with the outcome; the mediator and the outcome may be correlated because they are both caused by the initial variable *X*. Thus, the initial variable must be controlled in establishing the effect of the mediator on the outcome.

(4) Step 4. To establish that *M completely* mediates the *X*-*Y* relationship, the effect of *X* on *Y* controlling for *M* should be zero. Estimate and test the path *c'*. The effects of both Steps 3 and 4 are estimated in the same regression equation.

According to Baron and Kenny (1981), if all four of these steps are met, then the data are consistent with the hypothesis that *M completely* mediates the *X*-*Y* relationship, and if the first three steps are met but Step 4 is not, then *partial* mediation is indicated. Kenny, Kashy, and Bolger (1998) note, however, that meeting all four steps does not conclusively establish

that mediation has occurred since there may be other (albeit less plausible) models that are consistent with the data (MacCallum, Wegener, Uchino, & Fabrigar, 1993). Furthermore, they note that Step 4 does not have to be met unless the expectation is for complete mediation. Also, Step 1 is not required, but a path from the initial variable to the outcome is implied if Steps 2 and 3 are met. So the essential steps in establishing mediation are Steps 2 and 3.

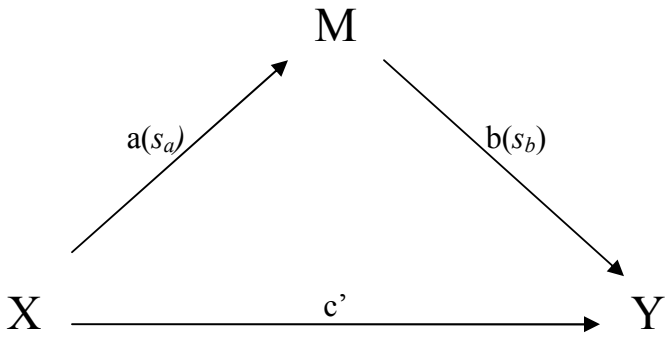
Shrout and Bolger (2002) also recommend setting aside Step 1 of Baron and Kenny's (1986) classic approach, due to the fact that more proximal $X \rightarrow M$ and $M \rightarrow Y$ associations are larger than the distal $X \rightarrow Y$ association. Because the test of the $X \rightarrow Y$ association may be more powerful when mediation is taken into account, it seems unwise to defer considering mediation until the bivariate association between *X* and *Y* is established. Instead, Shrout and Bolger (2002) recommend that for distal processes, for which the bivariate tests of association have limited power, mediation analysis proceed on the basis of the strength of the theoretical arguments rather than on the basis of the statistical test of *X* on *Y*. Relaxing Step 1 is especially important for developmental and other researchers who track long-term processes, as is the case in this study.

The amount of mediation is defined as the reduction of the effect of the intial variation on the outcome or $c - c'$. This difference in coefficients is equal to the product of the effect of *X* on *M* times the effect of *M* on *Y* or *ab* and so:

$$ab = c - c'.$$

If Step 2 and 3 are met, it follows that there necessarily is a reduction in the effect of *X* on *Y*. An indirect and approximate test that $ab = 0$ is to test that both *a* and *b* are zero (Steps 2 and 3). Baron and Kenny (1986) provide a direct test of *ab* which is a modification of a test

originally proposed by Sobel (1982). It requires the standard error of *a* or s_a (which equals a/t_a where t_a is the *t*-test of coefficient *a*) and the standard error of *b* or s_b. So:



where *a, b,* and *c* are the raw (unstandardized) regression coefficients, and the symbols s_a and s_b in parentheses are the (non-negative) standard errors of each path coefficient respectively.

The standard error of *ab* equals

$$SE_{ab} = \sqrt{s_a^2 s_b^2 + b^2 s_a^2 + a^2 s_b^2}$$

and so under the null hypothesis that *ab* equals zero, the following

$$\frac{ab}{\sqrt{s_a^2 s_b^2 + b^2 s_a^2 + a^2 s_b^2}}$$

is approximately distributed as *Z*. In most cases, however, the $s_a^2 s_b^2$ term is negligibly small and can be safely omitted, yielding:

$$SE_{ab} = \sqrt{b^2 s_a^2 + a^2 s_b^2}$$

Hence, following the recommendations from MacKinnon, Warsi, and Dwyer (1995), the significant of the indirect paths can be assessed using the modified Sobel test of indirect effects:

$$z - value = \frac{a * b}{\sqrt{b^2 s_a^2 + a^2 s_b^2}}$$

Since this test only works well for very large samples, it has been suggested that bootstrapping offers a much better alternative in that it imposes no distributional assumptions (Preacher & Hayes, 2004). Bootstrapping can be readily done with the AMOS software (Arbuckle, 2003). The results of both methods will be compared.

To model mediation in the present study, the Baron and Kenny (1986) approach will be adopted, with modifications to this approach as suggested by Kenny, Kashy, and Bolger (1998), Shrout and Bolger (2002) and others (e.g., Collins, Graham, & Flaherty, 1998). Specifically, because the present study is modeling long-term effects of contextual variables, the first criteria for mediation (direct effect of *X* on *Y*) as originally set forth by Baron and Kenny (1986) will be relaxed. Instead, it is expected that contextual socioeconomic stressors and Time 1 will significantly predict the parenting variables at Time 2, which will, in turn, significantly predict adolescent mental health at Time 3.

According to the classic Baron and Kenny (1986) strategy, each contextual stressor (negative life events, economic stress, and work stress) at Wave 1 is expected to *directly* predict adolescent mental health at Time 3 prior to adding mental health of parent and parenting practices at Time 2 into the model ($\beta_c > 0$). However, according to the strategy, this direct effect is expected to diminish significantly after adding mental health of parent into the model, which would suggest that the contextual effects have an indirect effect on adolescent mental health ($\beta_c = 0$, for complete mediation). In other words, the effects of contextual socioeconomic stressors on adolescent mental health are mediated through the parent's mental health and parenting practices. Also, following the analysis described in the previous

strategy, it is expected that parenting at Time 2 will have a significant indirect effect on adolescent mental health at Time 3, through the child's perception of parenting.

Strategy 3: Using multiple group analysis in SEM to test whether positive social support and spousal support moderate the effects of these contextual socioeconomic stressors on parent's and child's mental health and parenting practices

The moderating influences of spousal and social support are particularly important to the present study. According to the theoretical model (Figure 3), it is expected that social and spousal support will buffer the effects of the contextual socioeconomic stressors at Wave 1 on the parent's mental health and parenting behaviors at Wave 2 (Hypothesis 7). In addition, social support and spousal support are expected to buffer the effects of ineffective parenting behaviors at Wave 2 on the child's perception of parenting and the child's mental health at Wave 3 (Hypothesis 8).

According to Baron and Kenny (1986) one approach for modeling moderation is to simply create an interaction term, say between variable *X* and the moderating variable, called *M*, by multiplying the two terms together to create a new variable, *X***M*, then include this new interaction term in a regression equation, or as a predictor in a path analysis model (see Figure 6). According to this model, as described by Baron and Kenny (1986), there are three causal paths that feed into an outcome variable *Y*: the influence of a predictor (Path *a*), the influence of a moderator (Path *b*), and the interaction of these two (Path *c*). The moderator hypothesis is support if the interaction (Path *c*) is significant. There may also be significant main effects for the predictor and the moderator (Paths *a* and *b*), but these are not directly relevant conceptually to testing the moderator hypothesis. In addition, it is desirable that the

moderator variable be uncorrelated with both the predictor and the criterion (the dependent variable) to provide a clearly interpretable interaction term.

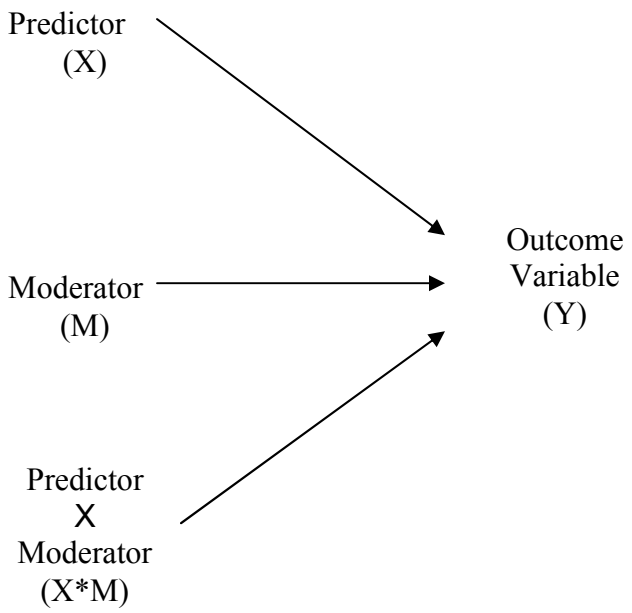


Figure 6. Moderator model.

Moderation is typically assessed with the regression equation:

$$Y = a_0 + a_1X + a_2M + a_3XM + r,$$

where M is the moderator. This expression may be rewritten as:

$$Y = (a_0 + a_2M) + (a_1 + a_3M)X + r,$$

clarifying how the simple slope of Y regressed on M, (a1 + a3M), is a function of the moderator. If a_3 is significant, the interaction effect may be examined futher to determine whether or not the simple slope of Y on X is statistically significant for chosen conditional values of M. This approach is described in detail by Aiken and West (1991). The quantity $(\hat{a}_1 + \hat{a}_3 M)$ may be divided by its standard error (*SE*) to yield a critical ratio test statistic distributed as *t* with $df = N - q$ in small samples (where q is the number of estimated regression coefficients), or *z* in large samples. The *SE* of the simple slope is:

$$SE_{(\hat{a}_1+\hat{a}_3W)} = \sqrt{s^2_{\hat{a}_1} + 2s_{\hat{a}_1\hat{a}_3}W + s^2_{\hat{a}_3}W^2}$$

The simple regressions of Y on Y at conditional values of W are also typically plotted to facilitate interpretation.

If *X* and/or *M* are interval-ratio variables, then they should be centered first before multiplying the terms together to reduce chances for multi-collinearity. Then estimate the regression using *X, M,* and *X***M* and check for influential points using Cook's *D* and/or DFBETAs for *X***M*. If the interaction is significant, we can graph it to help us with the interpretation of the moderation. This is a simple procedure when modeling using path analysis, but becomes prohibitive when using latent variable structural equation modeling with many indicators, although recent advance in software allows renders such modeling possible (e.g., M*plus*).

Another approach is to use multiple group or "stacked modeling" approach. According to this approach, the same structural model is estimated using two or more groups simultaneously. Multiple group analysis is useful for testing for differences in individual parameters, a factor model (CFA) for "test of factorial invariance," or an entire structural model for test of "measurement invariance" or "model invariance."

The procedure for conducting a multiple-group analysis for testing moderation is summarized as follows:

(1) Step 1. First specify the overall structural model, keeping the parameters that are of interest "free" or estimate freely. In other words, do not constrain a causal path, say from economic stress to mental health, to be equal for groups 1 (high spousal support) and group 2 (low spousal support)—denoted by $\gamma_{highsupport} = \gamma_{lowsupport}$.

Rather, freely estimate the path coefficients for both groups. Before proceeding to Steps 2 and 3, this model must first have adequate fit to the data, as measured by goodness-of-fit tests. The chi-square value for this freely-estimated model should be noted, as, for example, χ_{free}.

(2) Step 2. After obtaining an adequate model fit in Step 1, re-run this model constraining the parameters according to the relevant hypothesis. As an example, for the present study, the model can be run twice—once for the high spousal support group and another time for the low spousal support group—setting $\alpha_{highsupport} = 0$, and $\gamma_{highsupport} = \gamma_{lowsupport}$. Then note the chi-square value, denoted by χ_{fixed}.

(3) Step 3. Keeping in mind that chi-square is a measure of discrepancy between the sample covariance matrix and the model correlation matrix, a low chi-square value signifies that the model fits the data well. Hence, the primary question posed in the SEM hypothesis testing framework is: Did the model "deteriorate" significantly by imposing the constraints in Step 2? In other words, is the difference in the chi-square values for group 1 and group 2 significantly different? This difference can be statistically tested by testing the chi-square difference value for $\chi_{fixed} - \chi_{free}$. for one degree of freedom. If this difference is significant, then we reject the null hypothesis that the groups are equal and conclude that there is significant modulation in the causal path that can be accounted for by group differences, e.g., differences due to level of spousal support.

Following this procedure, causal paths that are significantly moderated by *M* can be found. In this study, *M* is level of spousal and social support.

Multiple group analysis will be conducted using SEM software, i.e., AMOS, to test for differences between groups (e.g., high and low spousal support) on each path. This will be accomplished by first fixing all factor loadings to be equivalent across groups and freely estimating all of the path coefficients. In the next step, one path will be restricted ("fixed") at a time, and the change in the chi-square value from the freely-estimated model to the restricted model will be noted. A significant chi-square difference (with 1 degree of freedom) between the two models will suggest significant moderation in that particular causal path by positive social and spousal support. Of greatest interest to this study is the buffering of the effects of economic stress, work stress, and negative life events on parent's mental health and parenting practices.

Strategy 4: Modeling the causal order between parents' mental health and parenting practices using growth curve, auto-regressive and cross-lagged modeling

Analysis of change in parenting and adolescent mental health is an important focus in the present study. However, most existing studies have been conducted using cross-sectional or only two waves of data, which limits detections in change. More recently, advances in statistical methods and availability of computational tools have lead to great strides in the analyses of longitudinal data. In addition to the classic regression or MANOVA and MANCOVA methods, autoregressive and latent growth curve methods have been widely used to model continuity and change in family research. These methods have certain advantages over traditional approaches. For example, using three or more waves of data, growth curve method is useful for modeling linear, quadratic, and higher-order change along with means. The latent growth curve design specifically incorporates two advantages—it

detects both intra-individual changes and inter-individual differences—one of the hallmark of life course perspective.

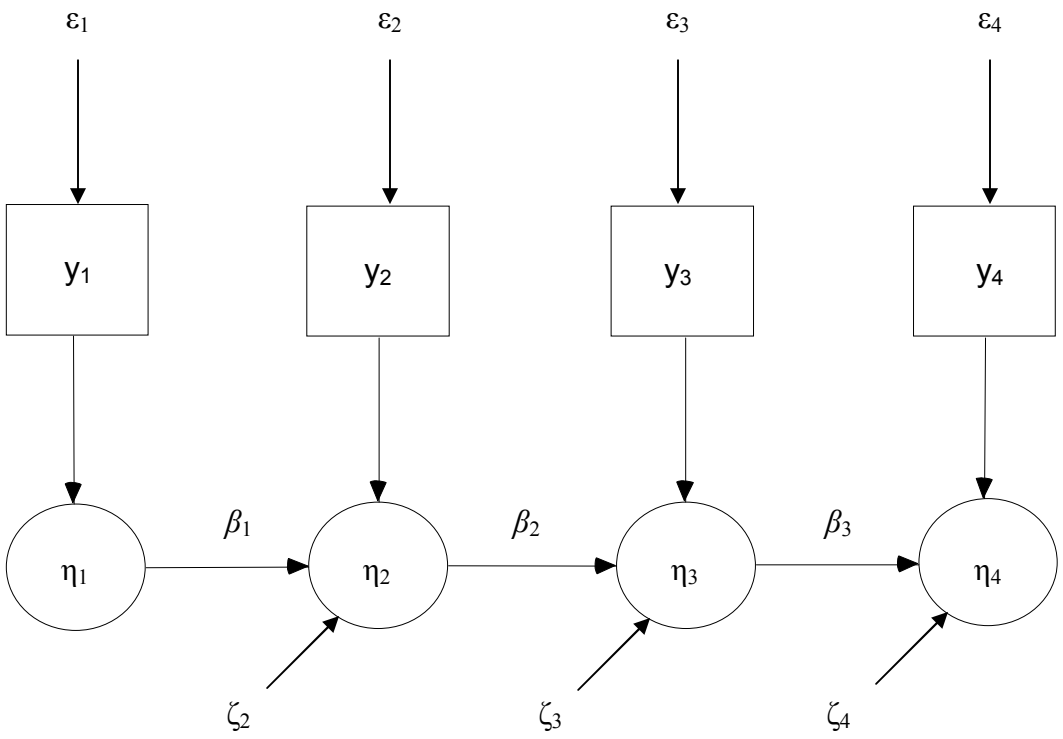


Figure 7. Autoregressive model.

Other than the latent growth curve method, approaches such as autoregressive models and repeated measures MANOVA have been used to model change. Structural equation modeling (SEM) and variations thereof has been extensively used for modeling change. Autoregressive, also called, "simplex," "quasi-Markov simplex," or "causal chain," modeling is one widely-used approach (see Jöreskog, 1970; see Figure 7). The simplest form of autoregressive model, as illustrated in Figure 7, explains the covariation from one time to another only by using the immediately preceding variables.

The benefit of the autoregressive models over growth curves is that explicitly estimate the stability of an attribute between points in time, whereas with growth curves high

stability is only implied when the variance of a slope is near zero. However, as Lorenz and colleagues (2004) note, this is not entirely satisfactory since variances of slopes can approach zero for reasons other than stability. In Figure 7, the regression coefficient linking subsequent latent measures (η_t) represents the stability coefficient. Ranging from -1 to +1, a high magnitude in the coefficient denotes high stability. Since this is just a bivariate regression coefficient, the square of the standardized regression coefficient is also the estimate of the variance explained (R^2) and also provide measure of reliability (λ_{ii}). In terms of matrix notation, the paths linking the latent variables to each other at fixed points in time can be denoted as follows:

$$\begin{bmatrix} \eta_{2i} \\ \eta_{3i} \\ \eta_{4i} \end{bmatrix} = \begin{bmatrix} \beta_1 & 0 & 0 \\ 0 & \beta_2 & 0 \\ 0 & 0 & \beta_3 \end{bmatrix} * \begin{bmatrix} \eta_{1i} \\ \eta_{2i} \\ \eta_{3i} \end{bmatrix} + \begin{bmatrix} \zeta_{2i} \\ \zeta_{3i} \\ \zeta_{4i} \end{bmatrix}.$$

The measurement equations linking the observed variables to the latent variables at each of the four points in time for each person can be expressed as a regression of the observed variables (y_{ti}) on the latent variables (η_{ti}) according to the model

$$y = \Lambda_y \eta + \varepsilon$$

or in matrix form:

$$\begin{bmatrix} y_{1i} \\ y_{2i} \\ y_{3i} \\ y_{4i} \end{bmatrix} = \begin{bmatrix} \lambda_{11} & 0 & 0 & 0 \\ 0 & \lambda_{22} & 0 & 0 \\ 0 & 0 & \lambda_{33} & 0 \\ 0 & 0 & 0 & \lambda_{44} \end{bmatrix} * \begin{bmatrix} \eta_{1i} \\ \eta_{2i} \\ \eta_{3i} \\ \eta_{4i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \\ \varepsilon_{3i} \\ \varepsilon_{4i} \end{bmatrix}$$

Just as in the latent growth curve model, the variances of the residual paths (e.g., ζ) are reflected in the diagonal elements of Ψ, whereas the error variances are again represented in the diagonal elements of Θ_ε. As it stands, the model is not identified. The convention way

to identify it is to impose constraints on the parameter estimates by setting the diagonal elements of the Λ_y matrix to 1.0 ($\lambda_{11} = \lambda_{22} = \lambda_{33} = \lambda_{44} = 1.0$) and by restricting the error variances in the Θ_ε matrix to be equal [$var(\varepsilon_1) = var(\varepsilon_2) = var(\varepsilon_3) = var(\varepsilon_4)$]. As specified, this model requires at least three waves of data before these restrictions are sufficient to be identified (Lorenz et al., 2004). Once the parameters are estimated, this model offers to insights not gained from cross-sectional analyses or from growth curves: (1) stability of an attribute between time points, and (2) reliability of measurement. The advantage of this approach over the traditional test-retest reliability approach is that this model relaxes the assumption of perfect stability and separate estimates of reliability from estimates of stability. When the model is identified by restricting the error variances to be equal, the solution to the equations leads to estimates of reliability (λ_{ii}) that are distinct from the estimates of stability (Lorenz et al., 2004).

Autoregressive models form the basis for techniques such as cross-lagged regression analysis (Kenny, 1979; Rogosa, 1979) and have been argued to be optimal modeling techniques for studying stability and change in developmental applications (e.g., Hertzog & Schaie, 1986; Jöreskog, 1979; Schaie & Hertzog, 1985). Despite its popularity and widespread use, autoregressive models are not without weaknesses, and must be used with caution (Hertzog & Nesselroade, 1987). One weakness is its omission of the means in the analysis of repeated measures. As McArdle and Epstein (1987) note, mean intercepts have been added onto autoregressive models, but these "regression adjusted means" are often of limited interest (Horn & McArdle, 1980; Jöreskog & Sörbom, 1979). In contrast, growth curve models can provide an integrated structure for the correlations, variances, *and* the means (McArdle, 1986; McArdle & Epstein, 1987). Critics point out that autoregressive

models are not only insensitive to individual differences in change over time, but also is fundamentally and statistically flawed in its core concept that an outcome variable can, in some sense, be "caused" by that same variable at an earlier time (Allison, 1990; Rogosa, Brandt, & Zimowski, 1982; Stoolmiller, Duncan, Bank, & Patterson, 1993; Lorenz et al., 1997). Critics argue that the study of change should describe individual growth or decline over time. For example, Rogosa et al. (1982, p. 744) explicitly state that "individual time paths are the proper focus for the analysis of change" (Lorenz et al., 1997). This sentiment is also shared by Hertzog and Nesselroade (1987) who question the universal validity of autoregressive models representing change over time in behavioral data and argue that dimensions along which individual differences are displayed are not homogeneous and uniform. They note that variables differ in two important ways: (1) temporal characteristics, and (2) antecedents of change. Traditional autoregressive models work best when variables are highly stable and have high temporal inertia (traits) rather than with variables that have low stability and are highly situational and temporally specific (states).

Essentially, the traditional regression method for analyzing change entails regressing the final measurement of symptoms on predictors after controlling for the initial level of symptoms. This is known as "residualized change scores" because covariates are used to predict residualized scores of the final measurement after removing the effect of initial measurement. Wickrama, Beiser, and Kaspar (2002) note several limitations of this approach. First, the non-dynamic nature of these models views psychopathology as a status rather than a process that unfolds over time (Coyn and Downy, 1991). Second, when individual change follows a non-linear trajectory, regression methods are unlikely to reveal intricacies of such change (Willet & Sayer, 1994). Moreover, "Ignoring the continuous

nature of change process, traditional methods prevent empirical researchers from entertaining a richer, broader spectrum of research questions, questions that deal with the nature of individual development" (Willet, 1988, p. 347; Wickrama, et al., 2002). That is, auto-regressive models take measurements as discrete time points, although change unfolds in a continuous manner (Karney & Bradbury, 1995; Wickrama, Beiser, & Kaspar, 2002). "Research questions with regard to the nature of change in psychiatric research—prodromal development of symptoms, in particular—requires researchers to view change as a continuous process using more than two time points, because the build-up of symptoms is a clinical process that may be non-linear and that has to be estimated with more than two time points. Moreover, this process may be systematically associated with sociocontextual and developmental processes" (Wickrama, Beiser, & Kaspar, 2002, p. 155).

In this consideration, one of the advantages of the latent growth curve approach over the autoregressive approach is that it focuses on the individual time path for analysis of change, as suggested by Rogosa et al. (1982). Latent growth curves combine elements of repeated measures MANOVA, confirmatory factor analysis (CFA), and structural equation modeling for modeling change over time. Unlike autoregressive methods, latent growth curves do not treat repeated measures as causes of themselves. Instead, they incorporate information about the means of observed indicators to estimate underlying time-related factors of growth and decline. These growth factors are sensitive to inter-individual differences in intra-individual change (Karney & Bradbury, 1995; McArdle, 1986; McArdle & Epstein, 1987; Meredith & Tisak, 1990; Rogosa et al., 1982; Willett & Sayer, 1994; Lorenz et al., 1997).

Univariate latent growth curves can be modeled as follows:

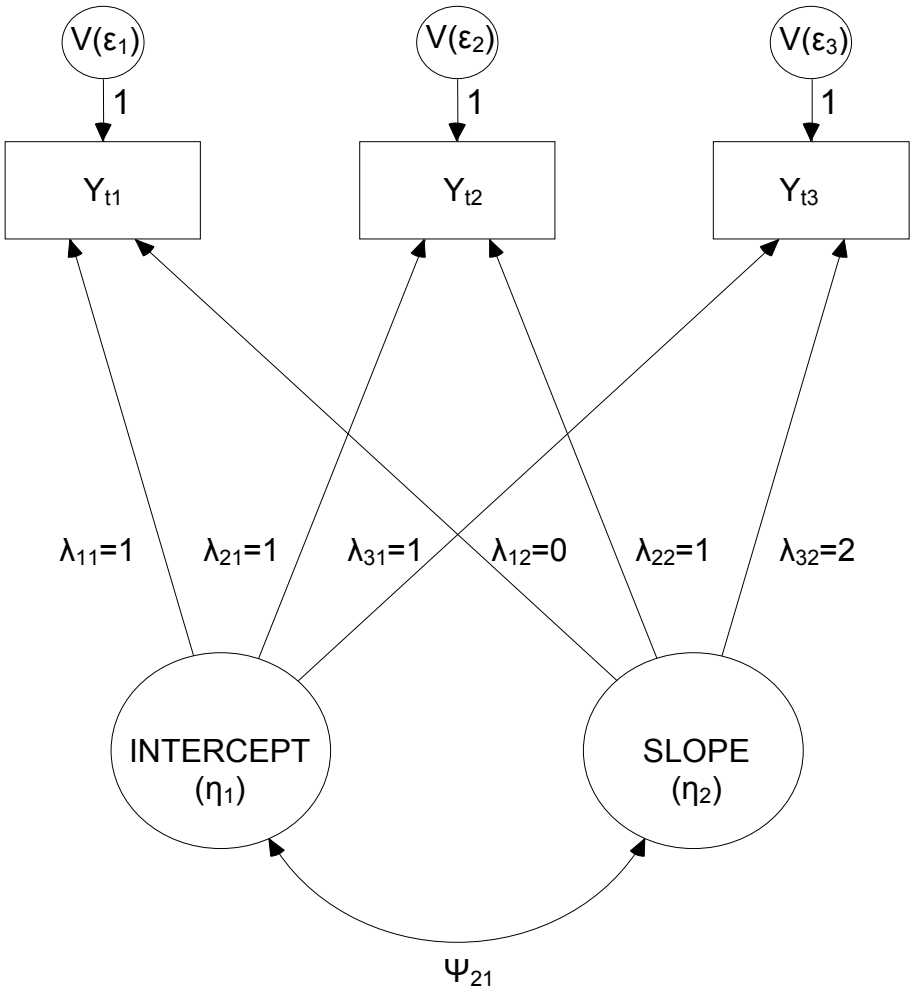


Figure 8. Univariate growth curve model.

In SEM matrix terminology, the general expression for latent trajectory modeling is:

$$y = \Lambda_y \eta + \varepsilon$$

In this terminology, y is a T x 1 vector of repeated (observed) measures, Λ is a T x k matrix of factor loadings, η is a k x 1 vector of latent factors, and ε is a T x 1 vector of residuals. Analogous to Level 2 growth curve equation, η can be expressed in terms of a mean and deviation as follows:

$$\eta = \mu_\eta + \zeta$$

where μ_η is a k x 1 vector of growth factor means and ζ is a k x 1 vector of residuals. Combining the previous two equations, a reduced-form matrix equation can be written as:

$$y = \Lambda(\mu_\eta + \zeta) + \varepsilon$$

This model is represented in Figure 8.

Variances of the observed repeated measures are:

$$VAR(y) = \Lambda\Psi\Lambda' + \Theta_\varepsilon$$

where Θ_ε represents the covariance structure of the residuals for the T-repeated measures of y and Ψ represents the covariance matrix of the deviations ζ. The mean structure of the observed repeated measures is represented as follows:

$$E(y) = \Lambda\mu_\eta$$

where Λ and μ_η are defined as before.

Univariate growth curves, using simple change scores and their intercepts, slopes and variances, can be also written as follows:

$$y_{ti} = \pi_{oi} + \pi_{1i}t + \varepsilon_{ti}$$

where i represents each individual ($i = 1 \ldots n$), with their own intercept (π_{oi}) and slope (π_{1i}) and error term (ε_{it}) for each individual at time t (t = 1, 2, 3). In hierarchical linear model framework, Raudenbush and Bryk (2002) express the individual growth trajectory as:

$$Y_{ti} = \beta_{oi} + \beta_{1i}x_{ti} + \varepsilon_{ti}$$

which is identical to the form above. This is often referred to as the level-1 equation. The intercept and slope parameters are random effects; in other words, they may vary across individuals, as reflected in the need for the i subscript denoting individual. This leads directly to the level-2 equations:

$$\beta_{0i} = \gamma_{00} + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + u_{1i}$$

Including these level-2 equations makes it a random-coefficients regression model. Say, for example, we have individual A with intercept β_{0A} and slope β_{1A}.The level-2 equations for this particular individual decompose the level-1 equation into two components: the grand mean of all the β_{0i}'s for all individuals, denoted by γ_{00}, and β_{0A}'s deviation from this grand mean, u_{0A}. Likewise, individual A's slope β_{1A} can be decomposed into two components: the grand means of all the β_{1i}'s for all individuals, γ_{10}, and β_{1A}'s deviation from this grand mean, u_{1A}. Interindividual variability in intercepts is expressed in the variance of the u_{0i}'s, and interindividual variability in slope is expressed in the variance of the u_{1i}'s. Curran (2003) has demonstrated that the hierarchical approach to growth modeling is in most cases identical to the structural equation model, or latent growth curve, approach (cf. Collins, 2006; McArdle & Epstein, 1987; Meredith & Tisak, 1990; Muthén & Shedden, 1999; Willett & Sayer, 1994).

In our case, using the notations for the two latent variables in Figure 3, the intercept (η_1) and slope (η_2) of the growth curve, and substituting $\eta_{1i} = \pi_{0i}$ and $\eta_{2i} = \pi_{1i}$, the first equation,

$$y_{ti} = \pi_{oi} + \pi_{1i}t + \varepsilon_{ti}$$

can be rewritten as:

$$y_{it} = \lambda_{t1i}\eta_{1i} + \lambda_{t2i}\eta_{2i} + \varepsilon_{it}$$

and individual response at each time point can be written as a series of equations:

$$y_{1i} = \lambda_{11i}\eta_{1i} + \lambda_{12i}\eta_{2i} + \varepsilon_{1i}$$

$$y_{2i} = \lambda_{21i}\eta_{1i} + \lambda_{22i}\eta_{2i} + \varepsilon_{2i}$$

$$y_{3i} = \lambda_{31i}\eta_{1i} + \lambda_{32i}\eta_{2i} + \varepsilon_{3i}$$

In matrix notation, the three equations can be rewritten as follows:

$$\begin{bmatrix} y_{1i} \\ y_{2i} \\ y_{3i} \end{bmatrix} = \begin{bmatrix} \lambda_{11i} & \lambda_{12i} \\ \lambda_{21i} & \lambda_{22i} \\ \lambda_{31i} & \lambda_{32i} \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \\ \varepsilon_{3i} \end{bmatrix}$$

The variances of the intercept [var(η_1) = Ψ_{11}] and slope [var(η_2) = Ψ_{22}], along with the covariance between them (Ψ_{21}), are given in the Ψ matrix:

$$\Psi = \begin{bmatrix} \Psi_{11} & \\ \Psi_{21} & \Psi_{22} \end{bmatrix}.$$

The error terms in this model are assumed to be normally-distributed with mean zero and with variances σ^2 (i.e., $\varepsilon_{ti} \sim NID(0, \sigma_{ti})$), and are represented by the diagonal elements of the Θ_ε matrix:

$$\Theta_\varepsilon = \begin{bmatrix} \Theta_{11} & 0 & 0 \\ 0 & \Theta_{22} & 0 \\ 0 & 0 & \Theta_{33} \end{bmatrix} = \begin{bmatrix} \sigma_{1i}^{\,2} & 0 & 0 \\ 0 & \sigma_{2i}^{\,2} & 0 \\ 0 & 0 & \sigma_{3i}^{\,2} \end{bmatrix}$$

The error terms in this model reflect the differences between the observed score and the predicted score for the each respondent at each of the three points in time.

According to Belsky (1984), parenting is determined by a multitude of forces. Specifically, according to the process model, the personal characteristics of the parent (i.e. psychological resources) determine parenting, rather than the opposite (Belsky, 1984). On the other hand, parenting efficacy theory suggests that undermined parenting and a sense of lack

of control over children may negative affect the parent's mental health, hence parenting self-efficacy has been included as one of the targeted areas of parenting interventions (cf. Cutrona & Troutman, 1986; Catalano, Berglund, Ryan, Lonczak, & Hawkins, 2004). Using a cross-lagged design, the reciprocal relationship between mental health and parenting will be explored in greater detail. The benefit of this design is that it offers insight into the relative strength of two or more time-varying covariates on each other (Lorenz et al., 2004):

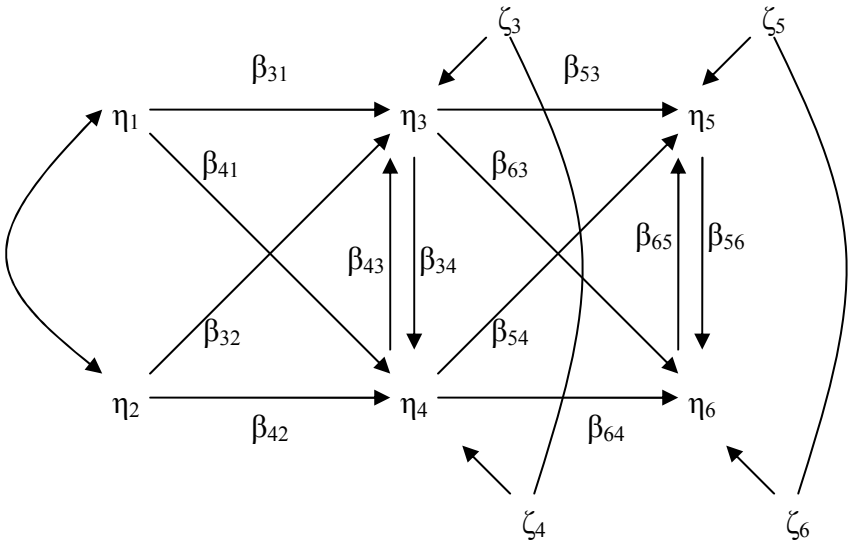


Figure 9. Three-wave, two-variable autoregressive model with both cross-lagged and contemporaneous effects.

In this model, the odd-numbered latent variables η_1, η_3, and η_5, are one attributed measured at Time 1, 2, and 3 respectively, and the even-numbered latent variables η_2, η_4, and η_6, are the second attribute measured at Time 1, 2, and 3. Just as in the auto-regressive model presented earlier in Figure 4, the path coefficients linking each latent variables (e.g., β_{31} and β_{53}) are the regression stability coefficients. Cross-lagged coefficients such as β_{41} and β_{32} represent the effect of one latent variable at time *t* on change in the second attribute at time *t+1*. In this sense, change is reflected in the magnitude of the residual that remains after regressing η_3 on η_1 and η_4 on η_2. The magnitude of β_{41}, along with β_{63}, can be compared to the magnitude of

β_{32} and β_{54} to gain insight into the extent to which the two variables reciprocate.

Contemporaneous effects can be modeled by adding paths (e.g., β_{34} and β_{43}) between latent variables within the same time frame (e.g., η_3 and η_4). However, adding contemporaneous effects to the model with cross-lags presents identification problem since there are just too many unknown parameters to estimate (Lorenz et al., 2004). As noted by Lorenz and colleagues (2004), one common method to address this problem is to impose restriction by assuming equality in the stabilities across time ($\beta_{53} = \beta_{31}$; $\beta_{64} = \beta_{42}$), in the cross-lags ($\beta_{63} = \beta_{41}$; $\beta_{54} = \beta_{32}$), and the contemporaneous effects (($\beta_{65} = \beta_{43}$; $\beta_{56} = \beta_{34}$). Another solution may be to model the reciprocal and cross-lagged effects separately:

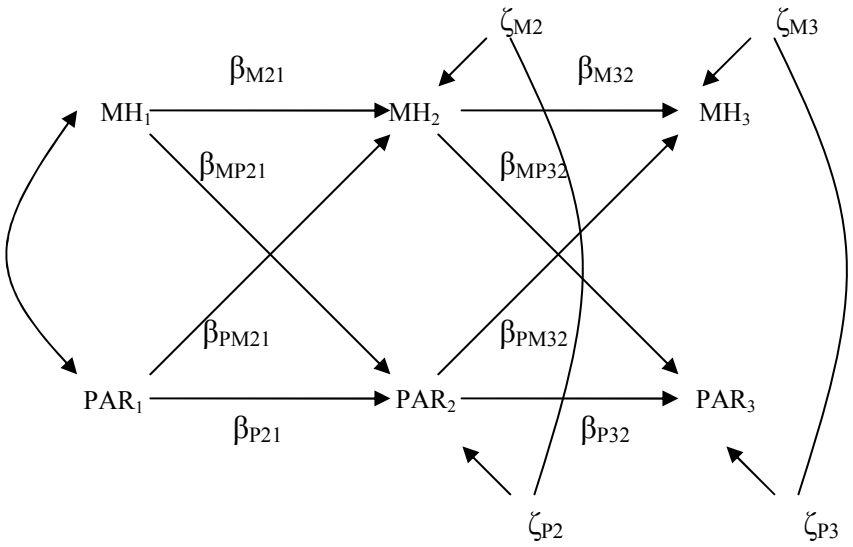


Figure 10. Cross-lagged model of parental mental health (MH) and parenting practices (PAR).

In the present study, cross-lagged coefficients such as β_{MP21} and β_{PM21} represent the effect of mental health at Time 1 on change in parenting at Time 2, and the effect of parenting at Time 1 on change in mental health at Time 2, respectively. By comparing the magnitude of the coefficients, the causal order can be established. According to the theoretical model, it is expected that parental mental health causes change in parenting (β_{MP21}

> β_{PM21}). Mental health is expected to be relatively more stable (β_{M21}, $\beta_{M32} \approx 0$) across time, while parenting practices show more variability and change over time (β_{P21}, $\beta_{P32} > 0$).

Similarly, the contemporaneous effects can be modeled separately as follows:

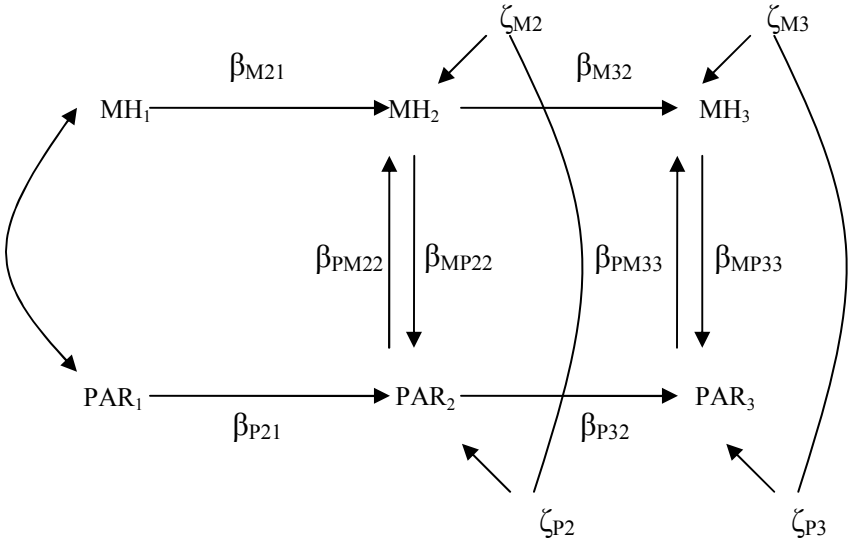


Figure 11. Contemporaneous model with correlated residuals.

For the present study, contemporaneous coefficient pairs such as β_{MP22} and β_{PM22}, and β_{MP33} and β_{PM33} represent the reciprocal relationship between parent's mental health and their parenting practices at Time 2 and Time 3 respectively. Comparing the magnitude of the coefficients sheds light on the extent to which these two variables reciprocate. According to the theoretical model, it is expected that parental mental health will have a stronger influence on parenting ($\beta_{MP22} > \beta_{PM22}$ and $\beta_{MP33} > \beta_{PM33}$).

Strategy 5: Using latent growth curves (LGC) and latent class growth analysis (LCGA) to model the dynamic association between parenting practices and adolescent mental health over time

As noted previously, one of the advantages of the latent growth curve approach is that it focuses on the individual time path for analysis of change, as suggested by Rogosa et al.

(1982). Latent growth curves combine elements of repeated measures MANOVA, confirmatory factor analysis (CFA), and structural equation modeling for modeling change over time. Unlike autoregressive methods, latent growth curves do not treat repeated measures as causes of themselves. Instead, they incorporate information about the means of observed indicators to estimate underlying time-related factors of growth and decline. These growth factors are sensitive to inter-individual differences in intra-individual change (Karney & Bradbury, 1995; McArdle, 1986; McArdle & Epstein, 1987; Meredith & Tisak, 1990; Rogosa et al., 1982; Willett & Sayer, 1994; Lorenz et al., 1997).

Another advantage of the LGC approach is that it incorporates growth parameters either as predictors or outcomes in the same model. Traditional regression approaches and MANOVA methods are unable to include all growth parameters (e.g., level and change) in the model simultaneously, both as independent outcomes of sociocontextual factors and predictors of later disorders. LGC models can also incorporate time-varying predictors of change in symptoms. As in the case of change in psychiatric symptoms, all aspects of change in predictors are important for understanding the associations with various aspects of change in symptoms. Differences in within-individual change in sociocontextual predictors across individuals may result in the differences in within-individual change in psychiatric symptoms across individuals (Wickrama et al., 2002). Thus, one possible analysis for the present study may be to relate differences in growth parameters (e.g., rate of change) of contextual socioeconomic variables across individuals to differences in growth parameters of mental health variables across individuals. Such an analysis would provide a richer and deeper understanding about the dynamic relationship between time-varying sociocontextual factors and mental health than traditional methods. In this regard, traditional regression approaches

and MANOVA methods are not capable of incorporating time-varying predictors and preserving their continuous nature. This is an important limitation for mental health research since the effects of contextual socioeconomic factors, such as the influence of life events and economic factors on mental health, are constantly changing.

The latent growth curve (LGC) technique within a structural equation modeling (SEM) framework fulfills the above needs in analyzing change. It provides an estimation of individual change parameters as well as their differences across individuals, and systematically relates these differences to the differences in time-invariant and/or time-varying predictors and in sequelae across individuals. The LCG capitalizes on the availability of data by taking into account both means and variance covariances. The SEM framework also provides a flexible approach to specifying random errors of measurements and their covariances. Moreover, as psychiatric research data sets become more and more complex with the addition of new waves of data and time-varying variables, the need for such a technique to analyze change is heightened.

Although a LGC approach within the SEM framework addresses several methodological issues related to the analysis of change, several potential limitations exist. First, although LGC provides estimates of individual specific growth parameters and examines systematic associations between growth parameters and other correlates, SEM is similar to traditional regression analysis in that the strength and nature of such associations are assumed to be the same for all individuals. Similarly, although the magnitude of growth parameters can differ across individuals, growth shapes (for example, linear) are assumed to be the same for all individuals. Realistically it is possible that individual differences in growth shape and associations between growth parameters and covariates exist. Second,

unlike in traditional regression analysis, regression parameters in SEM models should be interpreted acknowledging that some of the error terms in the model are allowed to correlate. However, extreme caution should be used when error terms are correlated in that such correlations should be theoretically or methodologically meaningful. Third, the statistical assumptions regarding distributional characteristics of the variables used in SEM are more restrictive. Specifically, SEM assumes univariate and multivariate normality of the variables. However, use of appropriate data matrices (for example, polychoric correlations) and appropriate fit indices (for example, the Satorra-Bentler scaled chi-square) to evaluate models effectively reduces influences due to deviations from multivariate normality. Moreover, study populations may be heterogeneous resulting in subpopulations requiring the use of multi-group SEM analyses. Finally, there are various fit indices available to evaluate SEM models. Those indices appropriate for any given model must be identified depending on factors such as sample size, number of variables, and deviation from distributional assumptions.

Fortunately, recent advances in methodological approaches and statistical software address the aforementioned limitations of traditional regression, autoregressive, and LGC approaches. Latent variable modeling software such as Mplus offers various modeling options that handle non-normality of data, discrete variables, and mixed modeling approaches. As Muthén and Muthén (2000) aptly put it, commonly used statistical approaches such as regression analysis, factor analysis, and structural equation modeling take a variable-centered approach to data analysis. Whereas studies using heterogeneous groups of individuals, as often the case with alcohol, drug, and mental health research studies, require person-centered approaches, such as cluster analysis, finite mixture analysis, latent class

analysis (LCA), latent transition analysis (LTA), latent class growth analysis (LCGA), growth mixture modeling (GMM), and general growth mixture modeling (GGMM).

A basic approach to modeling unobserved heterogeneity is latent class analysis (LCA). Conceptually, LCA is foundational to the more advanced approaches, such as LTA, LCGA, GMM, and GGMM. The concept of LCA was initially introduced by Lazarsfeld and Henry (1968) as a statistical method for finding subtypes of related cases (latent classes) from multivariate categorical data. The method was later formalized by Goodman (1974) and Clogg and Goodman (1984) who developed a maximum likelihood approach and provided some initial software. Currently, LCA is available in popular software such as Latent Gold (Vermunt, & Magidson, 2000), Mplus (Muthén & Muthén, 2004), and SAS PROC LCA (Lanza, Lemmon, Schafer, & Collins, 2006). See Appendix for Mplus and SAS examples of LCA.

LCA is a robust procedure in that it does not assume linearity, normal distribution of data, or homogeneity of variances. Also while LCA is most appropriate when the dependent variable is categorical it may also be used with ordinal data such as Likert scales, which are commonly used in social research, and with measurements with different scaling. Models may combine categorical and continuous variables. These are some of the advantages of the LCA procedure over traditional K-means and hierarchical clustering methods. In this sense, LCA is a form of mixture modeling, which refers to modeling with categorical latent variables that represent subpopulations where population membership is not known but is inferred from the data. Specifically, this is referred to as “finite mixture modeling” in statistics (McLachlan & Peel, 2000).

Conceptually, LCA is similar to cluster analysis (i.e., multivariate mixture estimation) in the sense that it is used to uncover groups or types of cases based on observed data and then assign individual cases to these latent groups. LCA is also similar to factor analysis in the sense that they are both data reduction techniques. However, the difference is that factor analysis is concerned with the structure of variables (i.e., correlations among variables), whereas LCA is more concerned with the structures of cases (i.e., classification of individuals). While there is clearly some connection between these two issues, LCA does seem more strongly related to cluster analysis than to factor analysis (Macmillan & Copher, 2005).

Latent classes are the dimensions which structure the cases with respect to a set of variables. It assumes that each observation is a member of one and only one *T* latent or unobserved classes and that manifest variables are independent of one another conditional on latent class membership, an assumption of local independence. So, when all latent classes are controlled, only a random relationship among variables remains. That is, latent class analysis divides the cases into latent classes which are "conditionally independent," meaning that the variables of interest are uncorrelated within any one class.

The model can be expressed in terms of the unconditional probabilities of belonging to each latent class and the conditional response probabilities for manifest variables given that latent class. The case of three manifest variables yields the following model:

$$\pi_{ijkt} = \pi_t^X \pi_{it}^{A|X} \pi_{jt}^{B|X} \pi_{kt}^{C|X},$$

where π_t^X denotes the probability of being in latent class $t = 1, 2, \ldots, T$ of latent variable X; $\pi_{it}^{A|X}$ denotes the conditional probability of obtaining the *i*th response to variable A from

members of class *t, i* = 1, 2, …, *I*; and $\pi_{jt}^{B|X}$ and $\pi_{kt}^{C|X}$, *j* = 1, 2, …, *J* and *k* = 1, 2, …, *K*, denote the corresponding conditional probabilities for variables *B* and *C*. The goal, then, is to identify the smallest number of latent classes that explain away all the associations between manifest variables.

As for assessing model fit, LCA employs many of the same model fit criterion as structural equation modeling, including BIC (Bayes information criterion), AIC (Aikaike information criterion) and CAIC (Consistent AIC, which penalizes for sample size as well as model complexity). These are goodness of fit measures which take into account model parsimony (that is, it penalizes for number of parameters in relation to maximum possible number of parameters). The lower the BIC, AIC or CAIC values, the better the model in comparison with another. Existing studies using LCA have frequently used BIC, with the best fitting model having the lowest BIC (cf. Guo, Wall, & Amemiya, 2006).

In mixture modeling with longitudinal data, unobserved heterogeneity in the development of an outcome over time is captured by categorical and continuous latent variables. The simplest longitudinal mixture model is latent class growth analysis (LCGA). In LCGA, the mixture corresponds to different latent trajectory classes. No variation across individuals is allowed within classes (Nagin, 1999; Roeder, Lynch, & Nagin, 1999). Another longitudinal mixture model is the growth mixture model (GMM). In GMM, within-class variation is allowed for the latent trajectory classes. The within-class variation is represented by random effects, that is, continuous latent variables, as in regular growth modeling (Muthén & Shedden, 1999; Muthén et al., 2002). Using structural equation modeling in Mplus, GMM for categorical outcome can be modeled as follows:

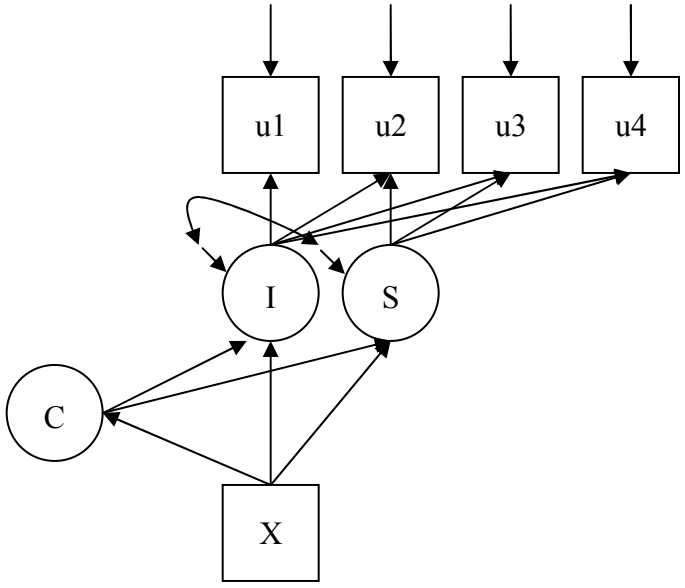


Figure 12. Generalized mixture model (GMM) for categorical outcome.

where *c* is the categorical latent variable, with growth factors *i* and *s*, for intercept and slope respectively. The arrows from *c* to the growth factors *i* and *s* indicate that the intercepts of the regressions of the growth factors on *x* vary across the classes of *c*. This corresponds to the regressions of *i* and *s* on a set of dummy variables representing the categories of *c*. The arrow from *x* to *c* represents the multinomial logistic regression of *c* on *x*. See appendix for example Mplus syntax for modeling GMM for a continuous outcome using automatic starting values with random starts.

Yet another mixture model for analyzing longitudinal data is latent transition analysis (LTA; Collins & Wugalter, 1992; Reboussin, et al., 1998), also referred to as hidden Markov modeling, where latent class indicators are measured over time and individuals are allowed to transition between latent classes. With discrete-time survival mixture analysis (DTSMA; Muthén & Masyn, 2005), the repeated observed outcomes represent event histories. For mixture modeling with longitudinal data, observed outcome variables can be continuous, censored, binary, ordered categorical (ordinal), counts, or combinations of these variable

types. Also, see Lanza, Collins, Schafer, and Flaherty (2005) for a good discussion of LCA and LTA.

As noted previously, several landmark studies have established that parenting affects child development in various ways (Belsky, 1984; Bowlby, 1988; Conger & Conger, 2002). One consistent finding from theoretical literature and subsequent studies using longitudinal data is that parenting has a long-term affect on the child's mental health. To model the long-term changes in both parenting and adolescent mental health, a growth curve model seems to be a sensible choice. First, the level and slope of both parenting practices and adolescent mental health will be first modeled using univariate latent growth curves:

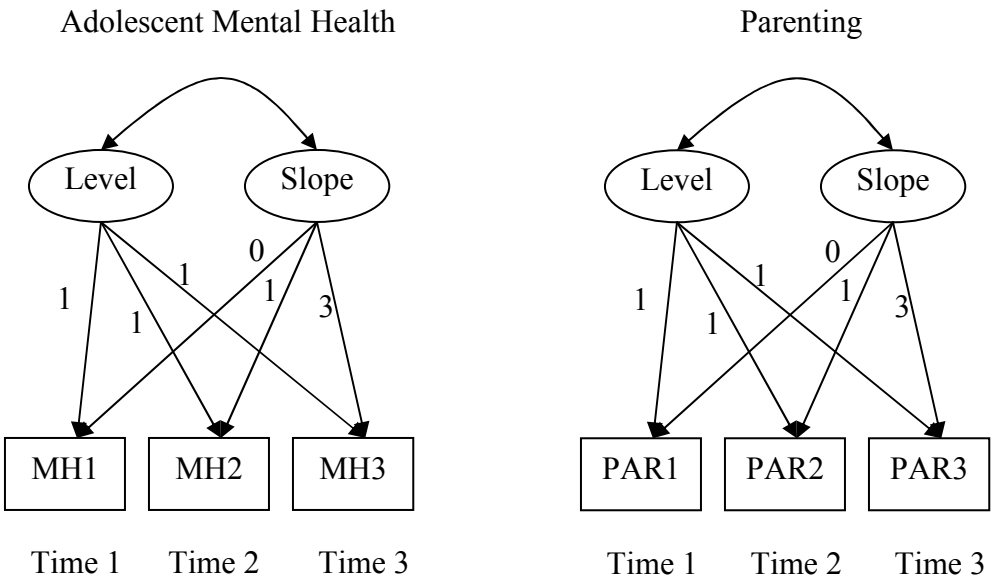


Figure 13. Univariate growth curve for parenting and adolescent mental health.

Then the two growth curves will be modeled together in an interlocking trajectory model so that the parenting growth model predicts the adolescent mental health growth model:

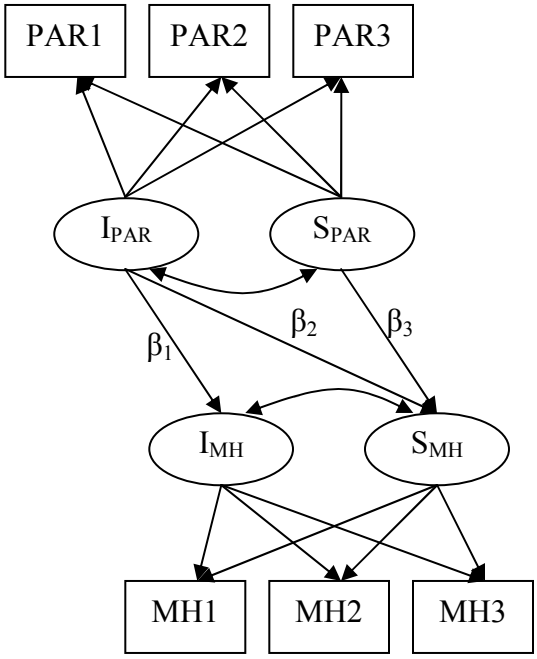


Figure 14. Interlocking trajectories of ineffective parenting and adolescent mental health.

According to the theoretical model, it is expected that change in parenting will significantly predict change in adolescent mental health. Specifically, the model in Figure 14 shows that high level (I_{PAR}) of ineffective parenting will be positively associated with high levels of poor mental health (I_{MH}; $\beta_1 > 0$) and increasingly poor mental health over time (S_{MH}; $\beta_2 > 0$). Furthermore, it is expected that an increase in the rate of change of ineffective parenting (S_{PAR}) will significantly predict a corresponding increase in the rate of change in poor adolescent mental health (S_{MH}; $\beta_3 > 0$).

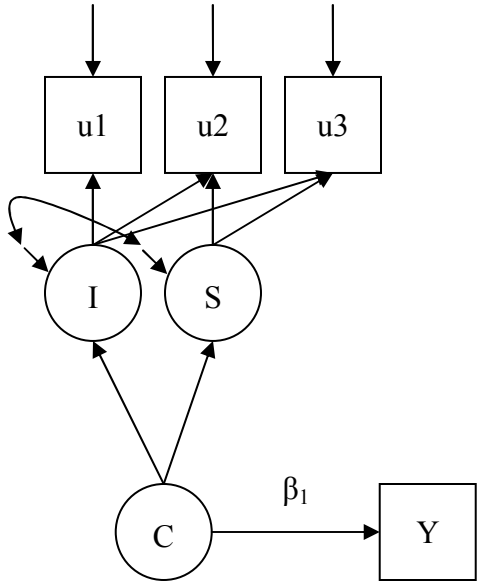


Figure 15. Latent class growth analysis (LCGA) with outcome variable Y.

Finally, latent class analysis growth analysis (LCGA) will be used to explore whether multiple trajectory classes of parenting emerge from the observed variance of intercept and slope (see Figure 15). Different classes ("C") of ineffective parenting (e.g., high, medium, low) with differing growth trajectories are expected to emerge. Furthermore, it is expected that class membership of parenting effectiveness will differentially predict levels of adolescent dichotomous mental health outcomes ("Y"; $\beta_1 > 0$).

CHAPTER 4: METHODS & PROCEDURES

Sampling Procedures and Measurement

Sample Characteristics

This study uses data collected from an existing study with single parent families in Iowa (see Simons, Beaman, Conger, & Chao, 1993). A sample of 210 female-headed households was recruited through the cohort of 8th and 9th grade students living in approximately two thirds of all counties in Iowa. University communities, and the counties contiguous to them, were excluded from the sampling frame. The sample was generated through lists of students provided by schools. The lists identified the name of each student's parent. Telephone calls were made to residences where the parent's name suggested the individual was female. Mothers were screened according to the criteria that they be permanently separated from their husbands, that the separation occurred within the past 2 years, that the husband from whom they separated was the biological parent of the eighth or ninth grade target child, and that they had a sibling within 3 years of age of the target child. These are rather stringent criteria, and only about 15% of the women telephoned met all of these requirements. Of the women who met the study criteria, an amazing 99% agreed to participate. Indeed, out of the 210 women recruited, only 3 later refused to be involved. This high response rate appeared to be a function of two factors: the women's need for the $175 subject compensation fee, and their desire to facilitate research concerned with the difficulties experienced by single-parent mothers.

Roughly a third of the families lived in communities smaller than a 7,500 population, another third resided in towns ranging in size from 7,500 to 50,000 residents, and the remaining third dwelled in cities larger than 50,000 inhabitants. Median family income,

including child support and government payments, was $21,521. Mean level of education was 13 years. Only 4% had not completed high school, 42% had some post high school training, and 16% had a college degree.

Procedures

Each family was visited twice at their home. During the first visit, each of the three family members completed a set of questionnaires focusing upon family processes, individual family member characteristics, and economic circumstances. On average, it took approximately 2 hours to complete the first visit. Between the first and second visits, family members completed questionnaires left with them by the first interviewer. These questionnaires dealt with information concerning beliefs about parenting and plans for the future. Each family member was instructed to place his or her completed questionnaire in an envelope, seal it and give it to the interviewer at the time of the second visit.

During the second visit, which normally occurred within 2 weeks of the first, the family was videotaped while engaging in several different structured interaction tasks. The visit began by having each individual complete a short questionnaire designed to identify issues of concern or disagreements within the family (e.g., chores, recreation, money, etc.). The family members were then gathered around a table and given a set of cards to read and discuss. All three family members were asked to discuss among themselves each of the items listed on the cards and to continue talking until the interviewer returned. The items on the cards concerned family issues such as discipline and chores, and the children's friends and school performance. The second task, 15 minutes in length, also involved all three family members. For this task, the family was asked to discuss and try to resolve the issues and disagreements which they had cited in the questionnaires they had completed earlier in the

visit. The third task involved only the two youths and was 15 minutes in length. The youths were given a set of cards listing questions related to the way they got along, the manner in which their parents treated them, their friends, and their future plans.

The family's interaction around these three tasks was videotaped. Interviewers explained each task and then left the room while the family members discussed issues raised by the task cards. During the time family members were not involved in a videotaped interaction task, each family member completed an additional questionnaire asking about significant life events, attitudes toward sexuality, and personal characteristics. The second visit lasted approximately 2 hours.

The videotapes were coded by project observers using the Iowa Family Interaction Rating Scales (Melby et al., 1990). These scales focus upon the quality of behavior exchanges between family members. The project observers were staff members who had received several weeks of training on rating family interactions and specialized in coding one of the three interaction tasks. Before observing tapes, coders had to independently rate precoded interaction tasks and achieve at least 90% agreement with that standard. For purposes of assessing interobserver reliability, 25% of the tasks were randomly selected to be independently observed and rated by a second observer. Reliability between observers was determined by calculating a generalizability coefficient. In the case of two independent observers, this coefficient is an intraclass correlation and provides an estimate of true score variance relative to error variance (Suen & Ary, 1989). The magnitude of this coefficient varied by rating scale but on average ranged between .60 and .70.

Measures

Per capita family income was calculated by dividing the total family income during calendar year 1991 by the number of parents and children living in the household. Per capital income of the single mothers averaged $7,060 in 1990, whereas the average for married mothers was $9,030 in the same year, a difference that was significant.

Support of former spouse. Four subscales (closeness, non-hostility, warmth, and marital quality) were used as indicators of "support of former spouse." The *closeness to former spouse* subscale consists of 10 items (e.g., "how much does he show concern for your feelings and problems," "how much would you say he understands the way you feel about things," "how much can you depend on your former spouse to be there when you really need him?") and had an alpha value of .84. The response format ranged from 1 (a lot) to 4 (not at all). Items were recoded so that higher scores indicated high levels of support from former spouse. The *marital quality with former spouse* subscale consisted of 2 items (e.g., "how happy are you, all things considered, with this relationship?" and "all in all, how satisfied are you with this relationship?") and had a correlation of .63. The *warmth and support of former spouse* subscale consists of 8 items (e.g., "how often did your former spouse…" "ask for your opinion about an important matter," "listen carefully to your point of view," "let you know he really cares about you"), and had an alpha value of .92. Using a response format ranging from 1 (always) to 7 (never), respondents were asked to rate how often they had experienced certain behaviors from their former spouse during the past 3 months. The *non-hostility and coercion of former spouse* subscale consisted of 12 items (e.g., "how often did your former spouse…" "get angry at you," "criticize you or your ideas," "show or yell at you because he was mad at you"), and had an alpha value of .94. Using a response format ranging

from 1 (always) to 7 (never), respondents were asked to rate how often they had experienced certain behaviors from their former spouse during the past 3 months. Items were recoded so that higher score indicated low hostility and coercion.

Social support. The tangible, appraisal, and belonging subscales of the Interpersonal Support Evaluation List (ISEL; Cohen & Hoberman, 1983; Cohen, Mermelstein, Kamarch, & Hoberman, 1985) were used as indicators of social support. The ISEL was developed as a measure of supportive social resources that facilitate coping with stressful situations (Cohen & Hoberman, 1983). The tangible subscale focuses upon perceived availability of instrumental assistance and had an alpha value of .77; the appraisal subscale is concerned with perceived availability of someone to talk with about one's problems and had an alpha value of .83; and the belonging subscale assess perceived availability of people with whom to do things and had an alpha value of .70. The ISEL has been shown to have strong internal consistency and to correlate with other measures of social support (Cohen et al., 1985).

Negative life events. Respondents were asked to indicate which of 23 negative events they had experienced during the previous 12 months. The events included incidents such as being laid off or fired, changing residence, death of a friend, unwanted pregnancy, getting robbed, losing one's driver's license, having an automobile accident, and the like. The events were summed to form an index score representing an accumulation of negative life events. Because cumulative number of unweighted life events consistently predicts adult psychological distress (Mirowsky & Ross, 1989), this measure was appropriate for estimation of the proposed theoretical model. The total score for this measure is the sum of the affirmative responses (1 = yes, 0 = no) for these events.

Work stress. Two subscales relating to job autonomy and job match were the indicators of work stress. The *bad job match* subscale consisted of 10 items (e.g., "this job matches my education and experience," "my job allows me to use my skills and abilities," "my job matches what I like to do") and had an alpha value of .87. Using a response format ranging from 1 (strongly agree) to 5 (strongly disagree), respondents were asked to rate how much they agreed on statements relating to their job and work experience. Items were recoded so that higher score indicated poor job match. The *job autonomy* subscale consisted of 9 items and has an alpha value of .75. The mother reported on questions such as, "I have a flexible work schedule"; "I am mostly my own boss"; and "I have a lot of opportunity to use my ideas and imagination in this job." Response categories ranged from 1 (strongly agree) to 5 (strongly disagree). Items were recoded so that a high score indicated low job autonomy.

Economic stress. On a scale from 1 ("strongly agree") to 5 ("strongly disagree"), participants were asked to rate the extent to which 16 statements about their financial well-being accurately described their current level of economic stress. Items included statements such as, "My family has enough money to afford the kind of home we would like to have," "We have enough money to afford the kind of food we should have," and "Our income never seems to catch up with our expenses." The response scale was recoded so that higher scores reflected a higher level of economic stress. The measure of economic stress was created by averaging the participants' responses across all 16 items. This scale had an alpha reliability of .87.

Ineffective parenting. Past research has established that ineffective parents do not set clear standards and do not communicate them to their children, are not consistent in enforcing rules, and practice harsh punishments (Maccoby & Martin, 1983). Research has

also shown that two dimensions of parenting are consistently highly correlated: positive emotional affect and effective parenting style (cf. Conger et al., 1992, 1993; Conger & Simons, 1997). For this reason, two domains of parenting are combined into a single latent construct (*nurturant-involved parenting*) with three empirical indicators (cf. Conger et al., 2000). High scores on these three dimensions were treated as indications of ineffective parenting.

The first indicator for the construct was parental affect, which was derived from observer ratings of parental warmth-support and hostility-coercion. Conceptually, parental affect is a continuum from a combination of very high hostility and low support expressed to the adolescent (the highest possible score) to a combination of very low hostility and high support expressed toward the adolescent (the lowest possible score). The measure of warmth and support was generated from task 1, which was designed, in part, to give the family the opportunity to express positive sentiments toward one another. The warmth and support scale was based on the summation of five observer ratings (a lower score indicates greater warmth and support): low communication, low assertiveness, poor prosocial behavior, low warmth-support, and listener non-responsiveness. The parental hostility and coercion toward the target youth measure consisted of summed ratings of hostility, antisocial behavior, and angry coercion demonstrated in task 2, designed to elicit conflict and anger. The alpha reliability for this first indicator was .90.

The second indicator was monitoring, which was the summed total of six observer ratings from task 1, designed in part to elicit information about parents' child rearing strategies: monitoring, positive reinforcement, consistent discipline, parental influence, quality time, and inductive reasoning. Items were recoded so that high scores reflected poor

monitoring. So, a parent who scores highly on this measure does not know what his or her child is doing, sets inappropriate rules and standards for conduct, inconsistently provides positive or negative contingencies for desired and undesired behaviors, does not spend time with the child in pleasurable activities, and does not encourage the child's understanding of the social consequences of his or her behaviors. The alpha reliability for this indicator was .64.

The third indicator for the ineffective (low nurturant-involved parenting) construct was harsh and inconsistent parenting. Patterson et al. (1992) suggested that parents who are inconsistent in their parenting practices, sometimes disciplining antisocial behavior and sometimes not, are more likely to have children with conduct problems. In response to these behavioral problems, parents in these families will increase their inconsistent and punitive actions in a fashion that leads to an escalating cycle of child misbehavior and parent harsh discipline and withdrawal from the child. The observer ratings for this indicator are intended to identify a parent who is high on this set of dysfunctional attributes. Four separate observer measures were summed to create an indicator of harsh and inconsistent parenting: inconsistent discipline, harsh discipline, indulgent discipline, and does not encourage independence. Thus, a parent who scores high on this indicator of parenting ineffectiveness will be inconsistent or harsh in disciplinary practices, will ignore misbehavior in a permissive fashion, and will withdraw from the child in a fashion that fails to encourage his or her autonomy and well-being. The alpha reliability for this indicator was .90.

Child's perception of parenting. The perception of parenting latent construct consisted of three indicators, each roughly corresponding to the three indicators of ineffective parenting (low nurturant-involved parenting) described above: low perceived closeness to

mother, poor relationship quality, and hostility. Using a 4-point scale (1 = "Often," 2 = "Sometimes," 3 = "Rarely," 4 = "Never"), subjects were asked to rate statements regarding their parent's parenting skills. The first indicator, low perceived closeness to mother, included items such as: "Make you feel tense while you are around her," "Act as if she is the only important person in the family," and "Expect more from you than she is willing to give". Scores were recoded so that high scores reflected low closeness to parent. The alpha reliability for this indicator was .87. The second indicator, poor relationship quality, included items such as: "Keep her promises to you," "Understand the way you feel about things," and "Make you feel you shouldn't tell her about things because she might be upset." Scores were recoded so that high scores reflected poor relationship quality. The alpha reliability for this indicator was .83. The third indicator, hostility, included items such as: "Cry, whine, or nag to get her way," "Ignores the problem," "Just seems to get angry," and "Argued with you whenever you disagreed about something." Scores were recoded so that high scores reflected high hostility. The alpha reliability for this indicator was .93.

Mental health. The depression, anxiety and somatic symptoms subscales of the SCL-90-*R* (Derogatis, 1983) were used as indicators of mental health for both the parent and the adolescent child. Past research has established the reliability and validity of this instrument (Derogatis, 1983). Using a response format ranging from 1 (not at all) to 5 (extremely), respondents were asked to rate how much they had experienced each symptom during the preceding week. The depression subscale consisted of 13 items (e.g., feeling blue, feeling no interest in things) and had an alpha of .94 for the parent at Time 2 and .88 for the child at Time 3 in the present study. The anxiety subscale consists of 10 items (e.g., feeling fearful, spells of terror or panic, feeling tense or keyed up) and had an alpha of .89 for the parent at

Time 2 and .89 for the child at Time 3 in the present study. The somatic symptoms subscale contained 12 items (e.g., headaches, faintness or dizziness, soreness of muscles, feeling weak in parts of your body) and had an alpha of .80 for the parent at Time 2 and .81 for the child at Time 3 in the present study. These three scales correlated significantly and were used as observed indicators of mental health for both the parent and the child.

Analytic Strategies

This study will use Strategies 1, 2, and 3, as described earlier to model the direct effects of contextual socioeconomic stressors on adolescent mental, the mediational processes of parent variables, and the moderational processes of spousal support and social support.

Methodological Issues

Missing Data

The problem of missing data will be addressed by using full-information maximum likelihood (FIML) in AMOS and Mplus. FIML is not available in LISREL, so mean-imputed data were used when models built in AMOS and Mplus were replicated using LISREL.

Attrition Analysis

The original sample size consists of 210 single-parent mothers at Time 1. The retention rates for Time 2 and Time 3 are 204 (97.14%) and 190 (90.48%), respectively. As mentioned previously, the missing data problem will be addressed by using full information maximum likelihood (FIML), to preserve the original sample size ($N = 210$) for the analyses. By using this missing data approach, the problem of attrition does not pose a significant threat to the analyses. In terms of sample size and power analysis, the smallest sample size of

190 at Time 3 would still suffice, if listwise deletion were to be used. However, listwise deletion will not be used in this study.

The effect of sample attrition can be examined by comparing attriters to those who remained in the study. Attriters can be identified by those who are missing one or more responses across the three waves of data collection. The sub-sample of attriters can be compared to those remaining in the study using independent *t*-tests for test of mean differences on the study variables. Significant differences in sample means will be noted where necessary.

CHAPTER 5: RESULTS

Introduction

This chapter presents the results of the analytic strategies as described previously in Chapters 3 and 4. First, descriptive statistics of the study sample is presented to draw attention to the unique background characteristics of the single-parent families in the study. Next a correlation matrix is presented to give an overview of the relationships among study variables that are pertinent to understanding the results of the latent variable analyses that will be presented later in the study. Finally, results of the latent variable analyses are presented, with particular emphasis given to the comparisons and contrasts among the different approaches. The results are presented in an order so as to build on preceding results and give deeper insight into the underlying mechanisms and intra-familial processes that comprise the family stress process.

Descriptive Statistics

Because this is a sample of recently divorced single-parent mothers, it may have unique characteristics which may help in understanding the processes through which socioeconomic contextual stressors impact the family. For example, as noted earlier, per capita family income (calculated by dividing the total family income during calendar year 1991 by the number of parents and children living in the household), of the single mothers averaged $7,060 in 1990, whereas the average for married mothers was $9,030 in the same year, a difference that was significant. At the beginning of the study, in 1991, the single mothers averaged $11,958. Also, only about 9% of the mothers had a bachelor's degree at Time 1 (see Table 2). From first glance, it is apparent that the stressors that single mothers face in this study sample are formidable.

The original sample size consists of 210 single-parent mothers at Time 1. The retention rates for Time 2 and Time 3 are 204 (97.14%) and 190 (90.48%), respectively. Notes from the field workers and follow-up questioning revealed that one of the major reasons for sample attrition was simply the fact that the single-parent mother had to move away in search of a job. Hence, economic-related stress is an influential factor in the lives of these single-parent mothers.

Table 2

Descriptive Statistics of Study Sample

		Wave 1 (1991)	*Wave 2* (1992)	*Wave 3* (1993)
Total sample size		210	204	190
Median number of children in household		3	3	3
Mean age of mother (in years)		38.88	39.52	40.39
Median Mother's education	*High School*	38.6%	33.7%	30.1%
	At least 1 year college	24.3%	26.4%	23.5%
	At least 2 years college	13.8%	14.0%	17.5%
	Bachelor's degree	7.1%	9.3%	12.6%
	Master's degree	1.9%	1.0%	1.6%
Median annual income		$11,958	$13,705	$16,061
Gender of child	*Females*	111	98	80
	Males	99	86	92
	Missing	0	20	18
Mean age of child		14.33	15.30	16.20
Child's grade in school	*8^{th} grade*	99	1	0
	9^{th} grade	111	87	4
	10^{th} grade	0	95	91
	11^{th} grade	0	0	76
	12^{th} grade	0	0	1

Table 3

Correlations Among Study Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Spousal Support	____																			
2. Social Support	.09	____																		
3. Negative Life Events	-.07	-.06	____																	
4. Economic Stress	-.12	-.29**	.42**	____																
5. Work Stress	-.01	-.21**	.22**	.32**	____															
6. Mother Depression	.05	-.31**	.11	.23**	.20*	____														
7. Mother Somatic Symptoms	.01	-.26**	.22**	.32**	.19*	.55**	____													
8. Mother Anxiety	.03	-.27**	.07	.21**	.13	.80**	.57**	____												
9. Observed Low Affect	.09	-.03	.12	-.00	-.05	.18*	.04	.13	____											
10. Observed Low Support	.01	-.30**	.18*	.22**	.10	.29**	.19**	.21**	.40**	____										
11. Observed Poor Monitoring	-.11	-.12	.05	.18*	.09	.20**	.08	.09	.23**	.37**	____									
12. Perceived Closeness	-.05	-.07	-.02	.08	-.23**	.01	.02	.00	.12	.18*	.25**	____								
13. Perceived Low Relationship Quality	-.06	-.09	.13	.21**	-.09	.027	-.02	.01	.06	.17*	.25**	.70**	____							
14. Perceived Hostility	-.13	-.13	-.02	.18**	-.03	.13	.07	.12	.20**	.29**	.23**	.74**	.61**	____						
15. Adolescent Depression (T1)	-.00	-.25**	-.02	.09	.00	.11	.00	.03	-.06	.09	.09	.30**	.20**	.27**	____					
16. Adolescent Anxiety (T1)	-.02	-.19**	-.02	.13	-.09	.09	.00	-.03	-.00	.16*	.15	.29**	.18	.30**	.76**	____				
17. Adolescent Somatic Symptoms (T1)	-.02	-.15*	.01	.11	-.05	.11	.01	.03	.12	.16*	.18*	.30**	.17*	.26**	.66**	.72**	____			
18. Adolescent Depression (T3)	.06	-.12	.07	.23**	-.03	-.01	.01	-.00	.00	.14	.11	.27**	.36**	.31**	.33**	.30**	.24**	____		
19. Adolescent Anxiety (T3)	.03	-.11	-.01	.14*	-.01	.05	.04	.04	.02	.15*	.20**	.26**	.34**	.31**	.41**	.41**	.32**	.83	____	
20. Adolescent Somatic Symptoms (T3)	.04	-.07	.06	.18*	-.02	.03	.03	.03	-.03	.17*	.14	.25**	.29**	.28**	.26**	.26**	.26**	.64**	.68**	___

$^{+}p < .10$, $*p < .05$, $**p < .01$ $***p < .001$

Figure 16 shows the overall measurement model. The fit indices suggest a good overall model fit. The chi-square value ($\chi^2 = 167.86$, $p < .001$) is highly significant, but is expected with larger sample sizes. In particular, a high CFI value of greater than .95 suggests good model fit (Hu & Bentler, 1999). Although this model has all significant factor loadings and significant paths, one hindrance to good model fit is the complexity of the model—this model includes 18 observed variables. One possible way to improve model fit is to simplify the model by reducing the number of indicators and reducing the total number of observed variables.

Table 4 displays zero-order correlations among theoretical constructs in later tests of the proposed model. The correlations show significant associations between Time 1 socioeconomic stressors and Time 2 parent variables. Of particular interest are the significantly positive associations between economic stress and all of the other study

Table 4

Correlations Among Constructs for the Overall Model

		1	2	3	4	5	6	7
1.	T1 Negative Life Events	__						
2.	T1 Economic Stress	.42***	__					
3.	T1 Work Stress	.23**	.33***	__				
4.	T2 Mother's Mental Health	.13^{+}	.26***	.21**	__			
5.	T2 Ineffective Parenting	.22*	.24*	.10	.37**	__		
6.	T3 Perception of Parenting	.01	.16*	-.19*	.05	.35**	__	
7.	T3 Adolescent Mental Health	.03	.19**	-.02	.04	.21*	.37***	__

$^{+}p < .10$, $*p < .05$, $**p < .01$, $***p < .001$

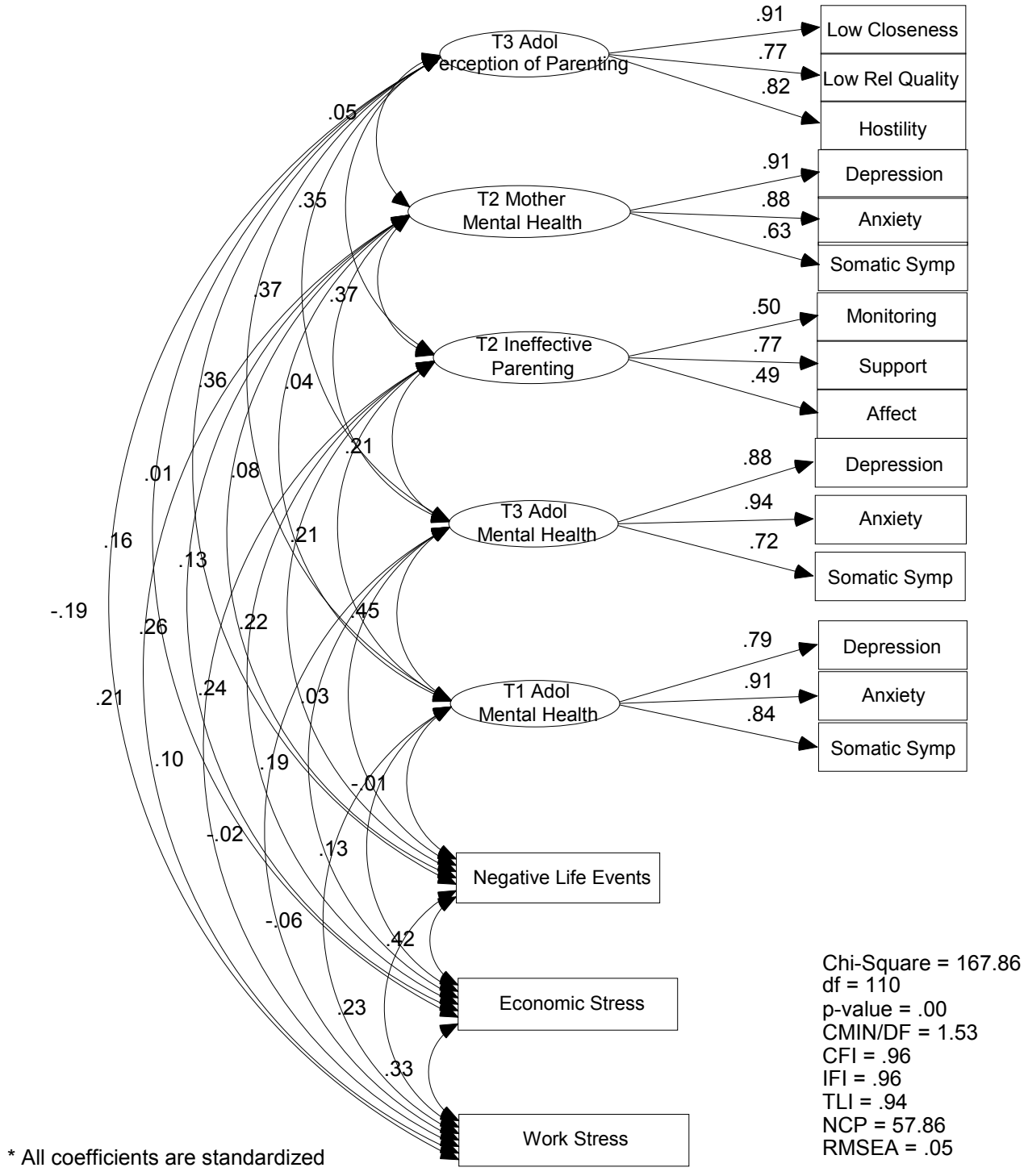


Figure 16. Overall measurement model.

variables. This suggests that economic stress plays a significant role in explaining much of the variance in the parenting and mental health measures and can be expected to be a significant predictor in the structural equation models in subsequent analyses. Most relevant to the hypothesized paths are the significant associations between Time 1 economic stress and work stress and Time 2 mother's mental health. These significant positive correlations suggest that increase in socioeconomic stressors contribute to an increase in the mother's reports of poor mental health symptoms and ineffective parenting practices. Also relevant to the hypothesized paths are the significant associations between Time 2 ineffective parenting variable and Time 3 adolescent variables. The significant positive coefficient suggests that an increase in ineffective parenting practices leads to an increase in the adolescent's reporting of poor mental health symptoms. Also interesting in the significant positive correlation between the trained observer ratings of videotaped ineffective parenting practices and the adolescent's self-reports of their observations of their mother's ineffective parenting practices. The fact that this correlation is significant but not extremely high shows that these two measures are related, but still distinct constructs. The larger coefficient between adolescent mental health and adolescent's perception of ineffective parenting than the observer ratings of parenting suggests that the adolescent's cognitive appraisal of their mother's ineffective parenting practices is a stronger predictor of their mental well-being than what may be considered "objective" assessment of parenting.

Figure 17 shows the test of direct effect of the contextual socioeconomic stressors at Time 1 on adolescent mental health outcome at Time 3. All the paths shown in this figure and all subsequent models were estimated by methods of maximum likelihood (Jöreskog & Sörbom, 1989). In this model and throughout the rest of the study, the correlated errors are

not shown in the diagram. The error terms of the three contextual stressors were correlated with one another. Also, the error terms of the three indicators of mental health at Time 1 were correlated with the corresponding measurement error at Time 3. Time 1 mental health error term was correlated with all other exogeneous variables (not shown). The results showed significant direct effect of economic stress ($\hat{\beta}$ = 0.16, t = 1.98), but no significant effects of negative life events ($\hat{\beta}$ = -0.02, t = -.28) or work stress ($\hat{\beta}$ = -0.04, t = -.48). This analysis shows the effect of economic stress on the residual change (after accounting for Time 1) in adolescent mental health at Time 3.

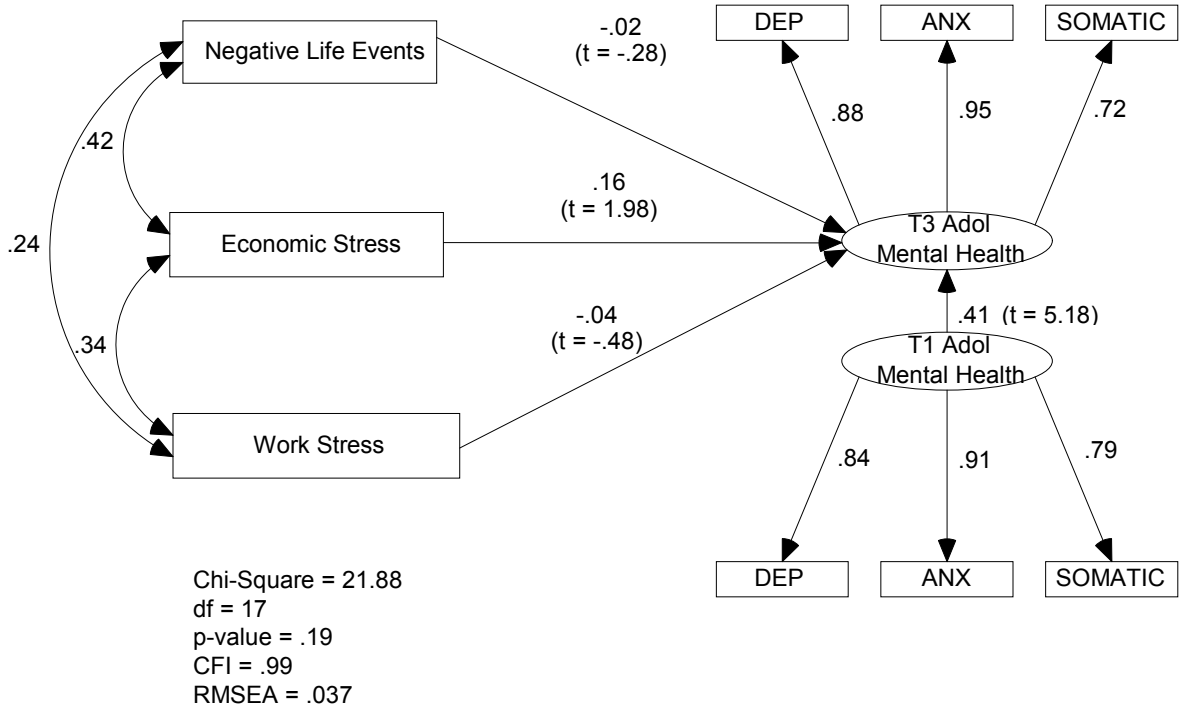


Figure 17. Test of long-term direct effect of negative life events, economic stress, and work stress on adolescent mental health (standardized estimates).

Test of Mediation of Contextual Socioeconomic Stressors on Parenting and Parental Mental Health

First a test of direct effect of contextual socioeconomic stressors on Time 2 ineffective parenting practices showed that only economic stress exerted a direct non-significant influence on parenting practices ($\hat{\beta} = 0.18$, $t = 1.72$).

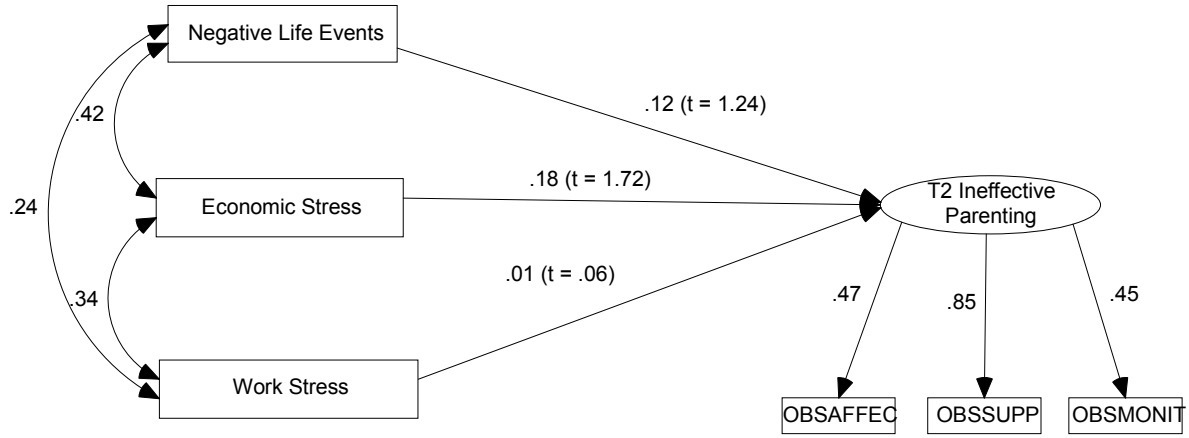


Figure 18. Test of direct effect of contextual socioeconomic stressors on time 2 ineffective parenting practices (standardized estimates).

To test for mediation, parental mental health was added to the model:

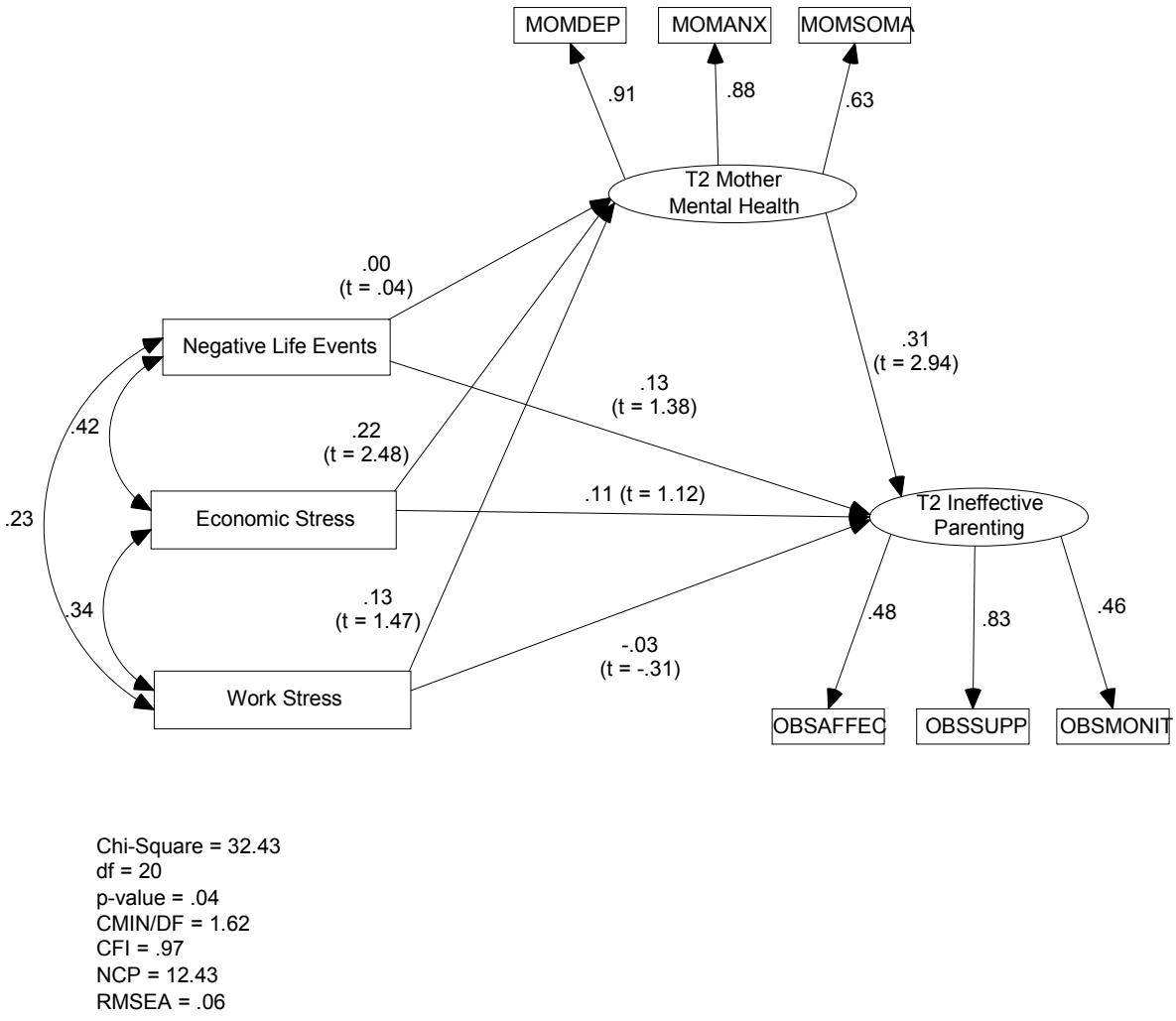


Figure 19. Test of indirect effect of contextual socioeconomic stressors on time 2 ineffective parenting practices (standardized estimates).

As expected, economic stress no longer exerted a significant direct effect on ineffective parenting, after including parental mental health in the model. This suggests that the effect of economic stress on parenting is mediated through the single parent mothers' mental health.

To test the significance of the indirect effect, the recommendations from MacKinnon, Warsi, and Dwyer (1995) are followed. Because this test is not available in AMOS, it was

calculated by hand. The significance of the indirect paths can be assessed using the modified Sobel test of indirect effects:

$$z-value=\frac{a*b}{\sqrt{b^2s_a^2+a^2s_b^2}}=\frac{.22*.31}{\sqrt{.310^2.029^2+.22^2.110^2}}=\frac{.0682}{.0285}=2.64$$

Based on the modified Sobel test of indirect effect, the z-score of 2.64 suggests a significant indirect effect of economic stress on ineffective parenting practices. Therefore, consistent with Hypothesis 1, economic stress at Time 1 had a significant direct long-term effect on adolescent mental health at Time 3. Furthermore, as hypothesized, economic stress significantly predicted Time 2 parental mental health. The loss of significant direct effect on adolescent mental health after adding Time 2 parent variables suggest that the long-term effects of economic stress is mediated through parental mental health and parenting practices. This was confirmed by the significant z-value as computed following Sobel's test of indirect effects.

The hypothesized direct effects of the other contextual socioeconomic factors, such as negative life events and work stress, were not observed. The positive coefficient suggests that the more economic stress the single mother experiences, the more likely she will develop symptoms of poor mental health (i.e., anxiety, depression, and somatic symptoms), which will in turn, negatively impact her parenting skills. The long-term end result is the increase in reports of symptoms of poor adolescent mental health: Increased anxiety, depression, and somatic symptoms.

Consistent with Hypothesis 2, poor parental mental health significantly predicted ineffective parenting practices. The positive coefficient suggests that the deterioration of

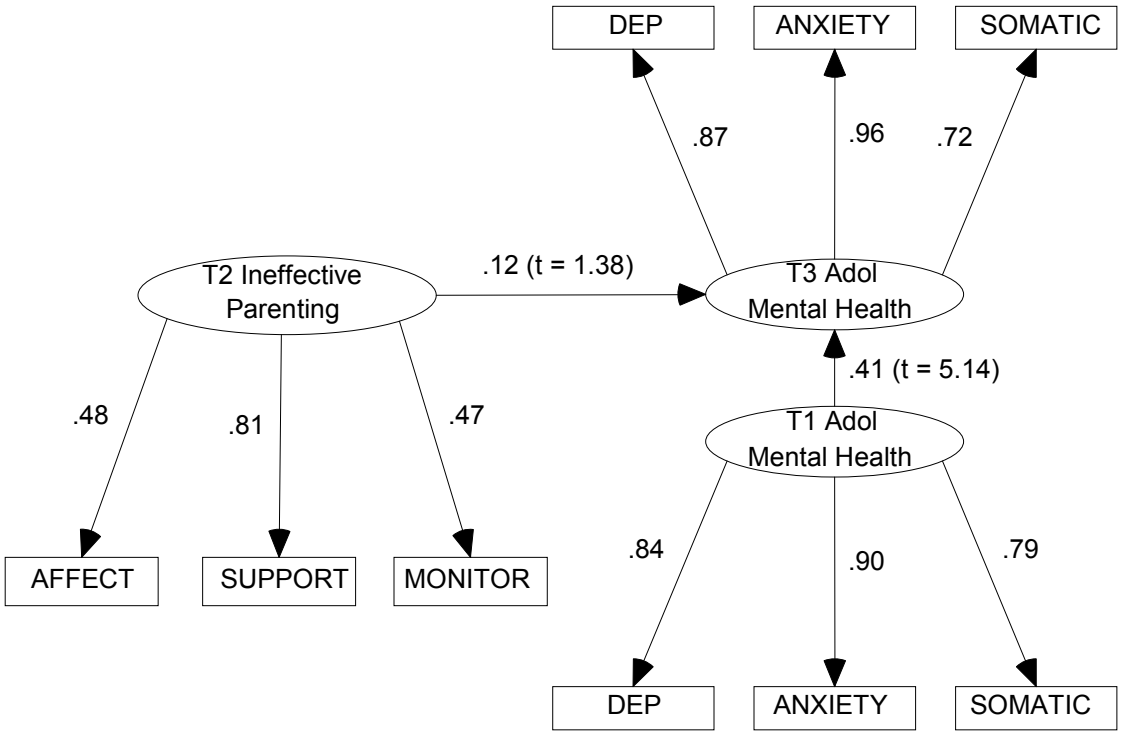
parental mental health leads to subsequent corresponding decline in effective parenting practices.

Consistent with Hypothesis 3, a test of direct effect of contextual socioeconomic stressors on Time 2 ineffective parenting practices showed that only economic stress exerted a direct, but only moderately significant, influence on parenting practices (Figure 18). As expected, economic stress no longer exerted a significant direct effect on ineffective parenting, after including parental mental health in the model (Figure 19). This suggests that the effect of economic stress on parenting is mediated through the single parent mothers' mental health.

Test of Mediation of Parenting on Adolescent Mental Health Through Perception of Parenting

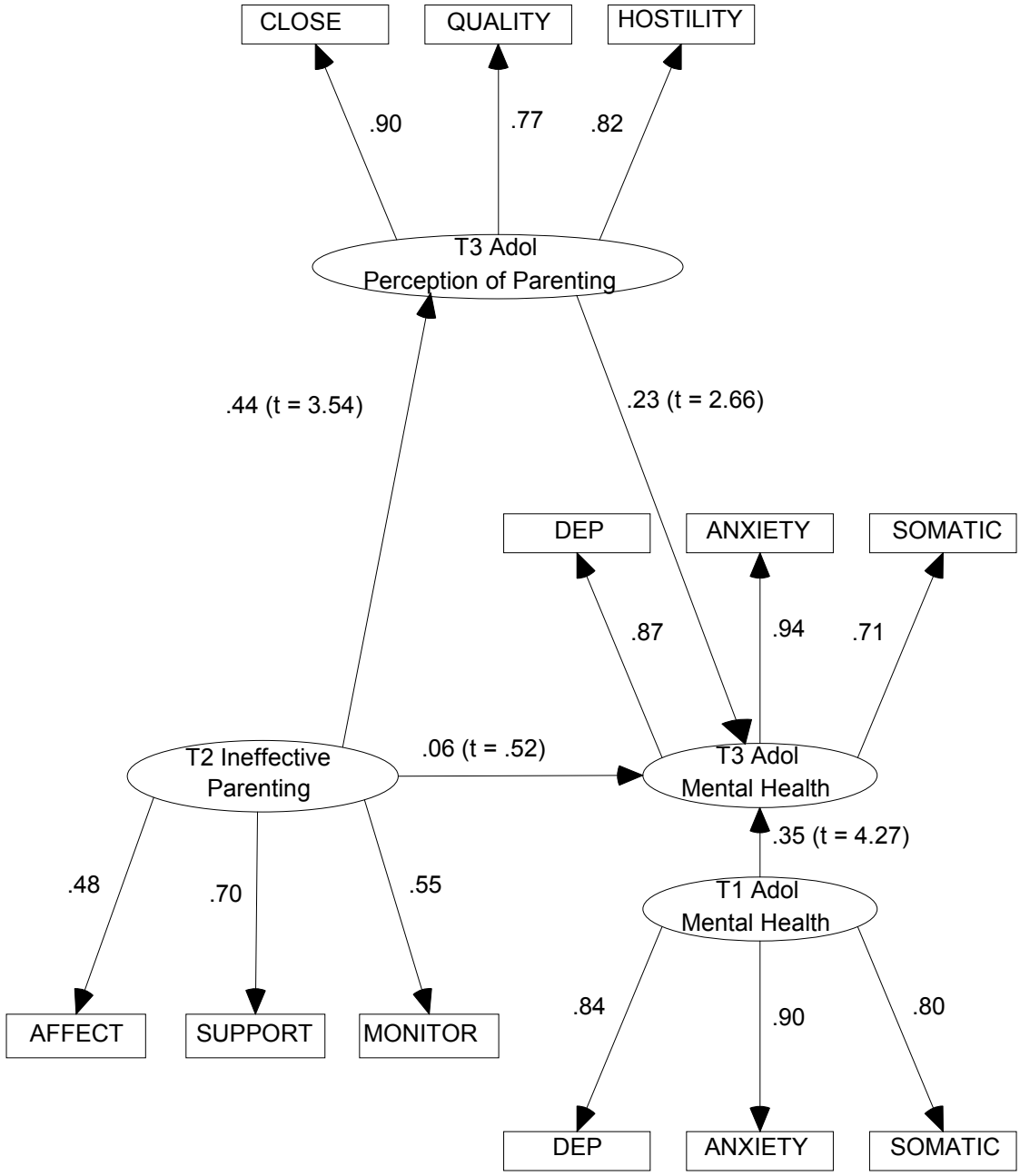
To test for direct effects of parenting practices at Time 2 on adolescent mental health and Time 3, adolescent mental health latent variable was regressed on parenting practices latent variable, controlling for Time 1 adolescent mental health (Figure 20). The error terms are not shown in the diagram, but the error terms for Time 1 mental health indicators variables were correlated with the respective errors in the Time 3 indicators. Furthermore, the error terms (not shown) of Time 1 adolescent mental health and Time 2 ineffective parenting were also correlated in both Figure 20 and Figure 21.

To test for mediation, adolescent perception of parenting at Time 3 was added to the model (Figure 21). After adding this mediating variable to the model, the path coefficient for the direct effect from Time 2 ineffective parenting to Time 3 adolescent mental health was tested for significance.



Chi-Square = 28.29
df = 21
P-value = .13
CMIN/DF = 1.34
CFI = .99
NCP = 7.293
RMSEA = .041

Figure 20. Test of direct effect of parenting practices on adolescent mental health.



Chi-Square = 76.03
df = 46
p-value = .004
CMIN/DF = 1.65
CFI = .97
NCP = 30.026
RMSEA = .056

Figure 21. Test of indirect effect of parenting practices on adolescent mental health.

Contrary to Hypothesis 5, there was no significant direct effect of parenting practices on adolescent mental health ($\hat{\beta}$ = 0.12, t = 1.38). However, consistent with Hypothesis 4, ineffective parenting at Time 2 significantly predicted the child's perception of parenting at Time 3 ($\hat{\beta}$ = 0.44, t = 3.54; see Figure 21). The significant positive coefficient ($\hat{\beta}$ = 0.44, t = 3.54) suggests that a positive change in ineffective parenting leads to a corresponding positive change in the adolescent's perception of their parent's parenting practices. Also, consistent with Hypothesis 6, the results show that the child's perception of parenting significantly predicts the child's mental health ($\hat{\beta}$ = 0.23, t = 2.66). The significant positive coefficient suggests that a positive change in perception of ineffective parenting leads to a corresponding positive change in the adolescent's mental health. The results collectively suggest that while child's perception may not mediate the effects of parenting practices on adolescent mental health in the traditional Baron and Kenny (1991) sense, parenting practices may still exert an indirect effect on adolescent mental health.

To test the significance of the indirect effect, the recommendations from MacKinnon, Warsi, and Dwyer (1995) are followed. The significance of the indirect path in Figure 21 can be assessed using the modified Sobel test of indirect effects:

$$z-value = \frac{a*b}{\sqrt{b^2 s_a^2 + a^2 s_b^2}} = \frac{.861*.258}{\sqrt{.258^2.243^2 + .861^2.097^2}} = \frac{.222138}{.10443} = 2.13$$

Based on the modified Sobel test of indirect effect, the z-score of 2.13 suggests a significant indirect effect of parenting practices on adolescent mental health. Therefore, while the direct effect of ineffective parenting on adolescent mental health was not observed, consistent with

Hypothesis 5, there was a significant indirect effect of poor parenting practices on adolescent mental health.

Figure 22 shows the result of the overall structural model. Adding the Time 2 parent variables resulted in the loss of significant direct effect of economic stress on adolescent mental health. This change suggests that the effect of economic stress on adolescent mental health is mediated through the parent's mental health and parenting practices.

In the maximum-likelihood estimation of the indicators of the Ineffective Parenting construct—low affect, low support, and low monitoring—have respective standardized loadings of .49, .77, and .50 in the overall model. The three indicators of Parental Mental Health—depression, anxiety, and somatic symptoms subscales of SCL-R-90—have respective loadings of .90, .88, and .63. The three indicators of Observed Ineffective Parenting—Poor Affect, Low Support, and Low Monitoring—have respective loadings of .49, .77, and .50. The three indicators of Perception of Parenting—Low Closeness, Low Quality, and Hostility—have respective loadings of .90, .77, and .82. The three indicators of Time 3 Adolescent Mental Health—depression, anxiety, and somatic symptoms subscales of SCL-R-90—have respective loadings of .87, .94, and .71. Finally, the three indicators for Time 1 Adolescent Mental Health—depression, anxiety, and somatic symptoms subscales of SCL-R-90—have respective loadings of .84, .90, and .79. All of the loadings of indicators on their latent constructs were statistically significant, with *t*-values ranging from 4.303 to 15.307.

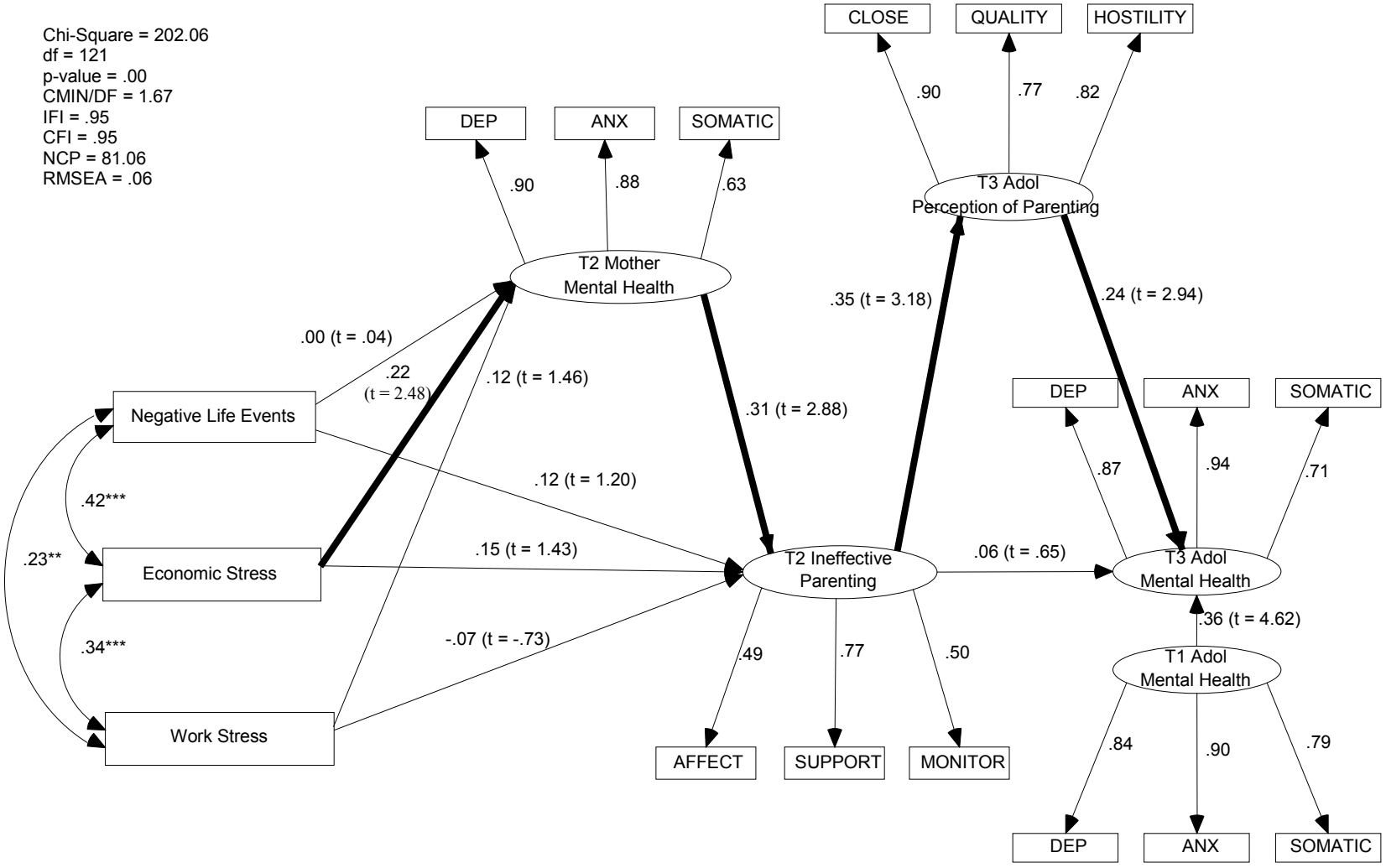


Figure 22. Standardized path coefficients for the full model.

Moderating Effects of Spousal Support and Social Support

Although this study is primarily interested in social support and spousal support as moderating variables, social support and spousal support are added to the model to examine whether these variables exert a direct effect on the parental mental health and parenting practices (Figure 23).

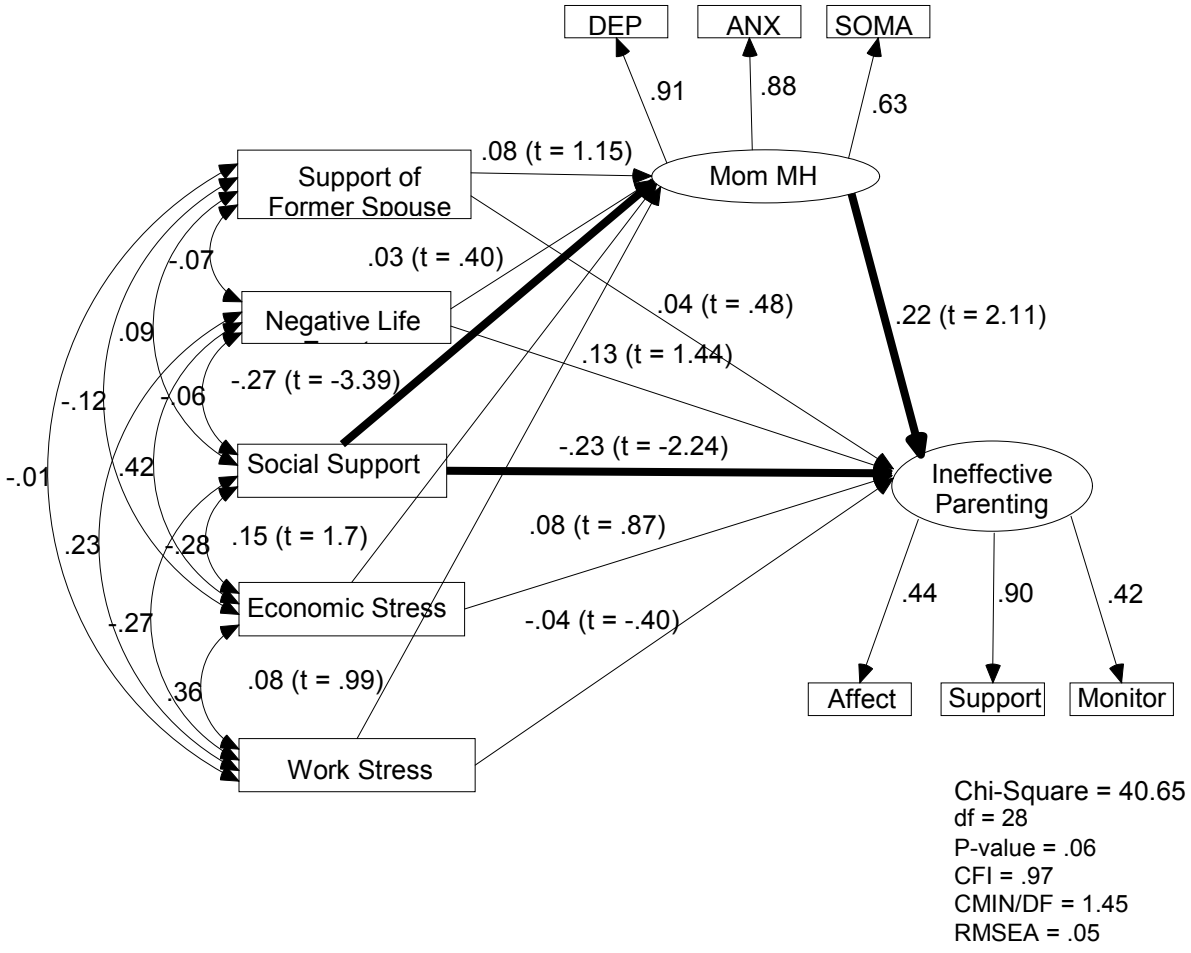


Figure 23. Direct effect of social support and spousal support on parental mental health and parenting practices (standardized estimates).

The analyses show that social support exerted a highly significant direct effect on parental mental health ($\hat{\beta}$ = -0.27, t = -3.39) and on parenting practices ($\hat{\beta}$ = -0.23, t = -2.24). Of the three negative contextual socioeconomic stressors, only economic stress exerted a non-significant direct effect on parental mental health ($\hat{\beta}$ = 0.15, t = 1.74), and did not exert a significant direct effect on parenting practices. Support of former spouse did not have a direct effect on parental mental health nor on parenting practices.

To test for the moderating effects of spousal support and social support, multiple group latent analysis was used to compare high- and low-levels of spousal support and social support samples. An examination of the correlation of the constructs (Table 5) shows preliminary differences in the associations depending on the level of support from former spouse.

Table 5

Correlations Among Constructs for High and (Low) Spousal Support Groups

	1	2	3	4	5	6	7
1. T1 Negative Life Events	—						
2. T1 Economic Stress	.38*** (.46***)	—					
3. T1 Work Stress	.19^{+} (.29**)	.30** (.36***)	—				
4. T2 Parental Mental Health	.03 (.20^{+})	.18^{+} (.33**)	.22^{+} (.13)	—			
5. T2 Ineffective Parenting	.14 (.32*)	.02 (.45**)	.15 (-.00)	.38* (.29^{+})	—		
6. T3 Perception of Parenting	.01 (-.00)	.06 (.21^{+})	-.24* (-.17)	.01 (.10)	.46** (.28^{+})	—	
7. T3 Adolescent Mental Health	.06 (.03)	.20^{+} (.19^{+})	-.01 (-.05)	-.05 (.09)	.30* (.15)	.40** (.30**)	—

$^{+}p < .10$, $*p < .05$, $**p < .01$, $***p < .001$.

Similarly, an examination of the correlation of the constructs shows preliminary differences in the associations depending on the level of social support (Table 6).

Table 6

Correlations Among Constructs for High and (Low) Social Support Groups

	1	2	3	4	5	6	7
1. T1 Negative Life Events	—						
2. T1 Economic Stress	.39*** (.47***)	—					
3. T1 Work Stress	.22* (.24*)	.40*** (.14)	—				
4. T2 Parental Mental Health	.14 (.12)	.25* (.22^{+})	.36** (-.05)	—			
5. T2 Ineffective Parenting	.21 (.23^{+})	.17 (.22)	-.01 (.14)	.21 (.39*)	—		
6. T3 Perception of Parenting	-.04 (.07)	.15 (.15)	-.24* (-.12)	.12 (.30)	.41* (.30*)	—	
7. T3 Adolescent Mental Health	-.08 (.11)	.08 (.27*)	-.08 (-.02)	-.05 (.05)	.12 (.22)	.34** (.39**)	—

$^{+}p < .10$, $*p < .05$, $**p < .01$, $***p < .001$.

The preliminary analysis of group differences among correlations of study variables show support for the hypothesis that the effects of socioeconomic contextual stressors are moderated by level of spousal and social support. In other words, there are differences in the effects of various environmental and social forces on the mental health and parenting practices of single-parent mothers and on the mental health of adolescents, depending on the level of spousal and social support experienced by the divorced single-parent mother. The differences in strength of association between high and low groups appear to be more noticeable between the high and low spousal support groups rather than between the high and

low social support groups. In particular, the results clearly show that the association between negative life events and economic stress and parent variables become stronger (worse) when there is lower spousal support (see Figure 5). These results suggest that the lack of support from ex-spouse exacerbates the negative effects of socioeconomic contextual stressors on the mother's mental health and parenting practices. Conversely, the results suggest that experiencing high levels of spousal support weakens (or buffers) the negative effects of the contextual stressors on the mother's mental health and parenting practices.

Although the correlational analyses show preliminary differences in the associations among the constructs depending on the level of social support and the support of former spouse, a more convincing analysis would be to test how significant these differences are. It is possible for an association to be just barely statistically significant for one group, but just barely not significant for another group. In this case, the correct conclusion would be that these two groups may not necessarily be statistically significant from *each other*. To test statistical significance between the two groups, we will conduct two separate analyses on the same model using the high versus low spousal support groups and examining changes in the overall model fit.

The primary purpose of this analysis is to examine the moderating role of social and spousal support in the effects of contextual socioeconomic stressors on parenting, and on parent and adolescent mental health. To test this hypothesis, these analyses are conducted separately for high versus low spousal support groups and again for high versus low social support groups. In the first analysis, we will test whether or not there are significant differences in the overall fit of the model. If the overall model fit between the two groups is

significantly different, then it would suggest that there are significant differences in the effects of the social and spousal support between the two groups.

In the second analysis, we will isolate differences in social and spousal support among the individual paths. To conduct these analyses, all structural parameters are allowed to vary in the first estimation of each model; then the individual paths are constrained to see whether this procedure would significantly reduce model fit. The loadings are held constant (invariant) across groups. A significant reduction in model fit would show that the path coefficients for each spousal support groups differ significantly.

For the first analysis, differences in overall model fit were assessed by first comparing groups with measurement loadings freed, then comparing the groups again with measurement loadings fixed (see Appendix 6A), using multiple group analysis in AMOS (Arbuckle, 2003). The analyses showed significant differences in the fully recursive model between the high versus low spousal support groups. The difference between the two groups showed a significant (p = .02) change in structural weights, with a chi-square value of 55.26, and 36 degrees of freedom change from the freely estimated model to the invariant paths model. These initial results support the hypothesis that moderation by spousal support may exist in influence of various social stressors on mental health and parenting practices. However, when fixing measurement weights, the significant findings in structural weights were not reproduced (see Table 7).

In the second multiple-group analysis, the same procedures were followed, except instead of testing for overall chi-square difference, each path were fixed one at a time to see whether the chi-square change contributed to a significant change in model fit. A significant

reduction in model would show that the particular path differs significantly across high and low spousal and social support groups, giving evidence for moderation effects.

Table 7

Nested Model Comparisons (High vs. Low Spousal Support)

Assuming Model Unconstrained to be Correct:

Model	DF	CMIN	P
Measurement weights	10	29.70	.00
Measurement intercepts	25	42.40	.02
Structural weights	36	55.26	.02
Structural means	39	58.28	.02
Structural covariances	45	60.09	.07
Structural residuals	50	69.66	.03
Measurement residuals	68	100.75	.01

Assuming Model Measurement Weights to be Correct:

Model	DF	CMIN	P
Measurement intercepts	15	12.70	.63
Structural weights	26	25.57	.49
Structural means	29	28.59	.49
Structural covariances	35	30.40	.69
Structural residuals	40	39.96	.47
Measurement residuals	58	71.05	.12

An examination of the individual paths (Appendix 6A & B) showed significant difference across the high and low groups for only the path leading from Time 1 economic stress to Time 2 ineffective parenting (Table 8).

Table 8

Change in Individual Path Estimate Across Levels of Spousal Support (High vs. Low)

	Path		Chi-square Change	Change in df
T1 Economic Stress	→	T2 Ineffective Parenting	5.14*	1

$^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

These results do not reflect the differences in correlations as observed earlier with the high versus low social and spousal support correlational analysis. This highlights the importance of conducting a separate multiple group analysis testing for significant group differences rather than merely identifying significant paths across groups. Consistent with Hypothesis 7, there is a significant difference in the influence of economic stress on parenting depending on the level of support of former spouse experienced by the single parent mother. However, contrary to the hypothesis, significant differences in the effect of parental mental health, negative life events, and work stress on parenting were not observed. In other words, there was no evidence that social and spousal support buffered the negative effects of work stress and negative life events on the mother's mental health and her parenting practices at Time 2. Also, contrary to Hypothesis 8, there was no evidence that social support and spousal support moderated the effects of ineffective parenting at Time 2 on the child's perception of parenting and the child's mental health at Time 3.

The results of the test of moderation showed that only the effect of economic stress on ineffective parenting was moderated by the level of support from former spouse. When the level of spousal support was low, economic stress had a significant impact on parenting

practices ($\hat{\beta}$ = .44, t = 2.99), but when the level of spousal support was high, there was no significant direct effect of economic stress on parenting ($\hat{\beta}$ = .06, t = 0.49; see Figure 24). Using multiple group analysis, the chi-square difference between the fixed and freely estimated models was calculated as follows: $\Delta\chi^2 = 5.14, p = 0.02$.

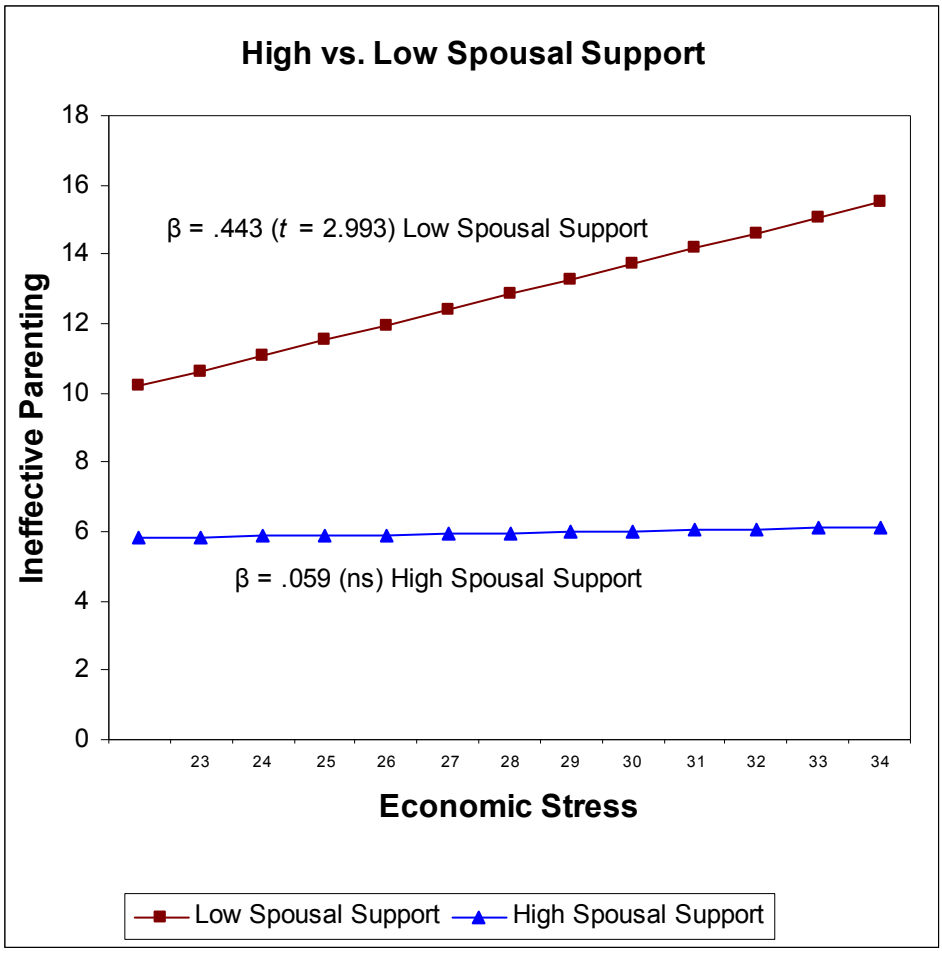


Figure 24. Economic stress and ineffective parenting (high vs. low spousal support).

Again, this finding is consistent with Hypothesis 7, that there will be a significant difference in the influence of economic stress on parenting depending on the level of support of former spouse experienced by the single parent mother.

Autoregressive, Cross-lagged, and Latent Growth Curve Models

In the full model, directional causal effects from parental mental health to ineffective parenting practices and from adolescent's perception of parenting to adolescent mental health are assumed on theoretical grounds, but measured within the same time period. To model change over time, other latent growth techniques such as auto-regressive, cross-lagged, and latent growth curve models can be used to assess both intra-individual change and inter-individual differences.

As discussed earlier, each analytic approach offers unique benefits to understanding the causal relationship among latent variables. In this section, each of the three approaches will be compared. A unique contribution of auto-regressive models over latent growth approaches is that they estimate the stability and reliability of a measure from one time to the next. Cross-lagged models extend the auto-regressive model by examining residual change (i.e., the amount of residual variance that is explained by another preceding variable.) However, one limitation to the autoregressive and cross-lagged approaches is that although these stability regression coefficients estimate the relative strength of the relation among latent variables over time, they do not explain mean-level change. In other words, it is possible for the means to increase, decrease, or stay the same without affecting the correlations or stability regression coefficients (Lorenz et al., 2004). These limitations will be illustrated in the following analyses.

As discussed previously, the latent growth curve design specifically incorporates two advantages—it detects both intra-individual changes and inter-individual differences—one of the hallmark of life course perspective. Specifically comparing latent growth curve method to

auto-regressive method, an advantage of the latent growth curve approach over the autoregressive approach is that it focuses on the individual time path for analysis of change, as suggested by Rogosa et al. (1982). Latent growth curves combine elements of repeated measures MANOVA, confirmatory factor analysis (CFA), and structural equation modeling for modeling change over time. Unlike autoregressive methods, latent growth curves do not treat repeated measures as causes of themselves. Instead, they incorporate information about the means of observed indicators to estimate underlying time-related factors of growth and decline. These growth factors are sensitive to inter-individual differences in intra-individual change (Karney & Bradbury, 1995; McArdle, 1986; McArdle & Epstein, 1987; Meredith & Tisak, 1990; Rogosa et al., 1982; Willett & Sayer, 1994; Lorenz et al., 1997). The results of auto-regressive, cross-lagged, and latent growth curve models are reported below.

The auto-regressive model for mother's mental health (Waves 1 to 3) shows high stability across time. To identify the model, the error variances were constrained to be equal as well as the loadings for each indicator across the three waves of measurement. The stability coefficients from Wave 1 to Wave 2 and from Wave 2 to Wave 3 are .75 and .85 respectively, suggesting high stability (Figure 25). Furthermore, the highly significant factor loadings across time suggest high reliability.

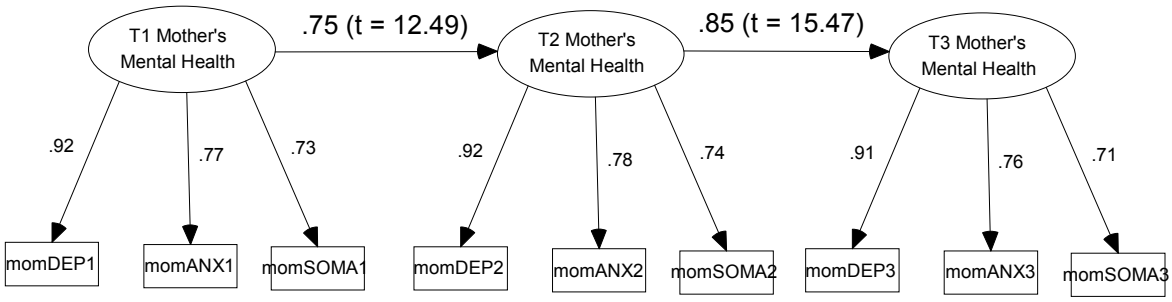


Figure 25. Auto-regressive model for mother's mental health (waves 1 to 3).

The auto-regressive model for parenting practices was identified in a similar fashion as the auto-regressive model for mother's mental health. Because of the absence of Wave 3 data for observer ratings for parenting practices, only Waves 1 and 2 are modeled in the auto-regressive model (Figure 26).

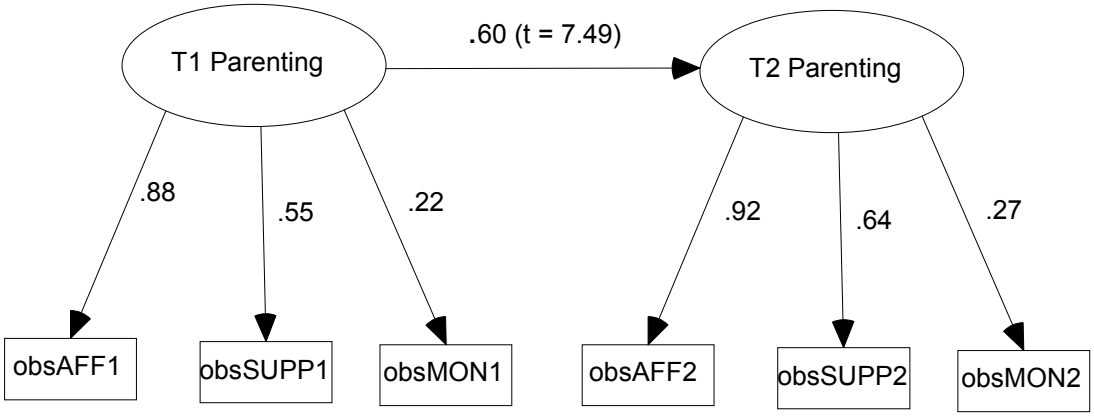


Figure 26. Auto-regressive model for ineffective parenting (waves 1 to 2).

Just as in the auto-regressive model for mother's mental health, the path coefficient and loadings were all significant. The coefficient value of .60 suggests moderately high stability (Figure 26).

Using Waves 1 and 2 only for mother's mental health and parenting practices, the two auto-regressive models are combined to test for causality using cross-lagged and contemporaneous models (Figure 27).

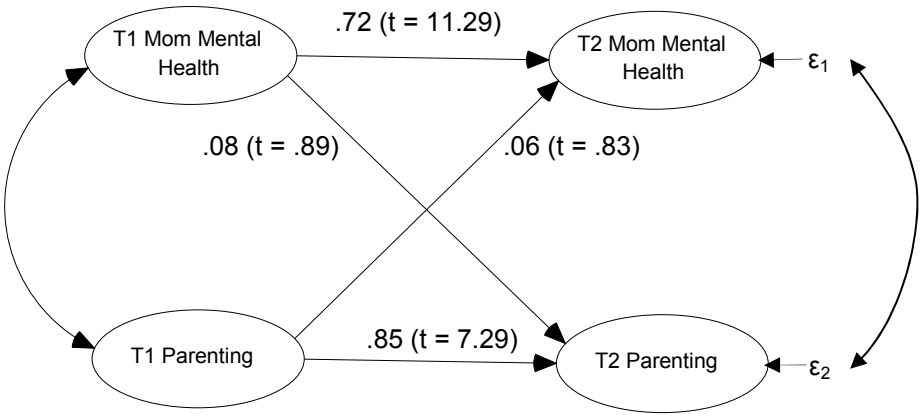


Figure 27. Cross-lagged model for mother's mental health and ineffective parenting.

The results of the cross-lagged model did not support the hypothesis that there would be a direct effect of mother's mental health on parenting and vice-versa. Contrary to what was initially expected, the cross-lagged coefficients from mother's mental health to parenting and from parenting to mother's mental health—0.06 and 0.05, respectively—were both statistically non-insignificant. However, as mentioned previously, a limitation of cross-lagged models is that it is attempting to measure residual change, and does not explain mean-level change. Because the mental health and parenting variables are highly stable, there is very little residual change to explain.

Consistent with the cross-lagged model, the results of the contemporaneous model did not show evidence for contemporaneous reciprocal relationship between mother's mental health and ineffective parenting (Figure 28). There were no significant contemporaneous reciprocal effects between mother's mental health and parenting practices at Wave 2. Again, the reason for the lack of significant effects is that the variables are highly stable and does not explain mean-level change.

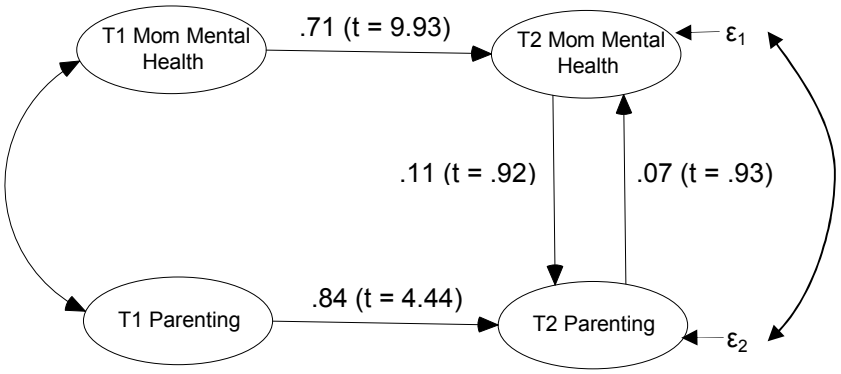


Figure 28. Contemporaneous model for mother's mental health and ineffective parenting.

The models thus far examined the effects of time-invariant covariates on patterns of intra-respondent change in a time-varying attribute. As illustrated in the analyses, a limitation of the autoregressive and cross-lagged models is that it measures residual change and not mean-level change. Latent growth curve models addresses the weaknesses of these approaches examined thus far.

In the next section, latent growth curve models are used to examine the effects of a second time-varying covariate. In terms of a human development framework, this approach allows one to examine the longitudinal covariation of one family member's change in behavior or feelings with the changes in the same behaviors and feelings of another. To estimate interlocking trajectories between mothers' mental health and her parenting practices, univariate growth curve models for mental health (Figure 29) and parenting practices are estimated separately first.

To model the univariate growth curve model for mothers' mental health, a second-order multiple-indicator linear growth model for continuous outcomes as shown in Figure 29 was estimated by maximum likelihood estimation using both Mplus and AMOS. Although

both programs give identical solutions, they differ in the output provided to the user. For example, in this analysis and for subsequent latent growth analyses, AMOS was used to estimate the overall measurement model and factor loadings, while Mplus was used to assess overall model fit (i.e., obtain SRMR) and obtain estimates of the mean intercepts and slopes of the growth factors. Also, Mplus can do general mixture modeling, such as latent class analysis, while AMOS and LISREL lack the capability. So the results of both software programs are provided in the figures. To achieve successful estimation, the slope at Time 3 and the factor loadings were free estimated. In addition, the residual error variances and intercepts for the indicators were fixed to equality [$var(e_1)= var(e_2)= var(e_3)=...= var(e_9)=12.47$]. The results

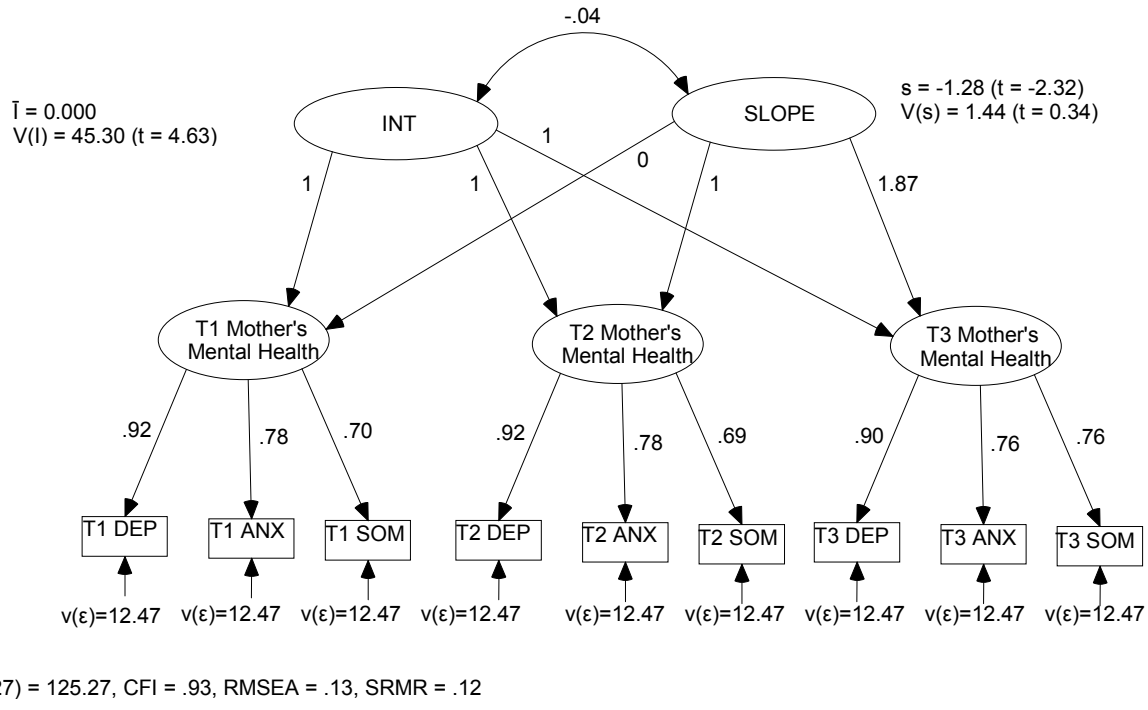


Figure 29. Univariate growth curve for mothers' mental health (waves 1-3).

showed significant negative slope for mother's mental health, suggesting a gradual, but significant decline. This finding is consistent with univariate descriptive statistics of mother's mental health, showing a decrease across time for all three indicators of mental health (see Table 9). This suggests that mother's mental health is improving with time. A closer examination of each of the three measures of mother's mental health—depression, anxiety, and somatic symptoms—show the gradual improvement in all three indicators of mother's mental health (Table 9).

Table 9

Univariate Statistics for Indicators of Mother's Mental Health

Indicator	N	Mean	SD	Variance
T1 Depression	208	23.32	8.90	79.21
T2 Depression	193	21.67	9.33	87.14
T3 Depression	189	20.24	8.10	65.54
T1 Anxiety	208	14.32	5.14	26.38
T2 Anxiety	193	13.81	5.31	28.15
T3 Anxiety	189	13.15	5.02	25.16
T1 Somatic Symptoms	208	17.06	5.49	30.09
T2 Somatic Symptoms	193	16.78	5.11	26.12
T3 Somatic Symptoms	189	16.51	5.73	32.88

Significant variance in the intercept (t = 4.63) and significant mean slope (t = -2.32) are observed. However, there is no significant variance in the slope factor, suggesting relatively uniform change across time among the individuals. Because the variance of the

slope factor is non-significant, there is no need for further analysis of the growth factors using latent class growth analysis.

In terms of overall model fit, the chi-square value of 125.27 with 27 degrees of freedom suggests a poor model fit. Although the CFI fix index is good (.93), RMSEA and SRMR are above acceptable levels, suggesting a poor model fit. One reason for the poor model fit in this case is that there are simply too many free parameters to estimate given the limited sample size ($N = 210$). Also, constraining the intercepts and residual errors to equality often results in poorer model fit.

Next, a univariate growth curve for ineffective parenting was specified (Figure 30). Because only two waves of data were available for modeling observed parenting behavior, this presented difficulty with modeling longitudinal change. Given only two points in time, it is impossible to explicitly state whether the underlying change process is linear, quadratic, logarithmic, or exponential. Any of these change models can conceivable fit the data. Having three or more waves of data helps delineate the pattern of growth. Given only two waves of data, it was necessary to fix the residual errors to zero to estimate the growth parameters. A chi-square value of approximately 727.70 with 2 degrees of freedom suggests a poor model fit.

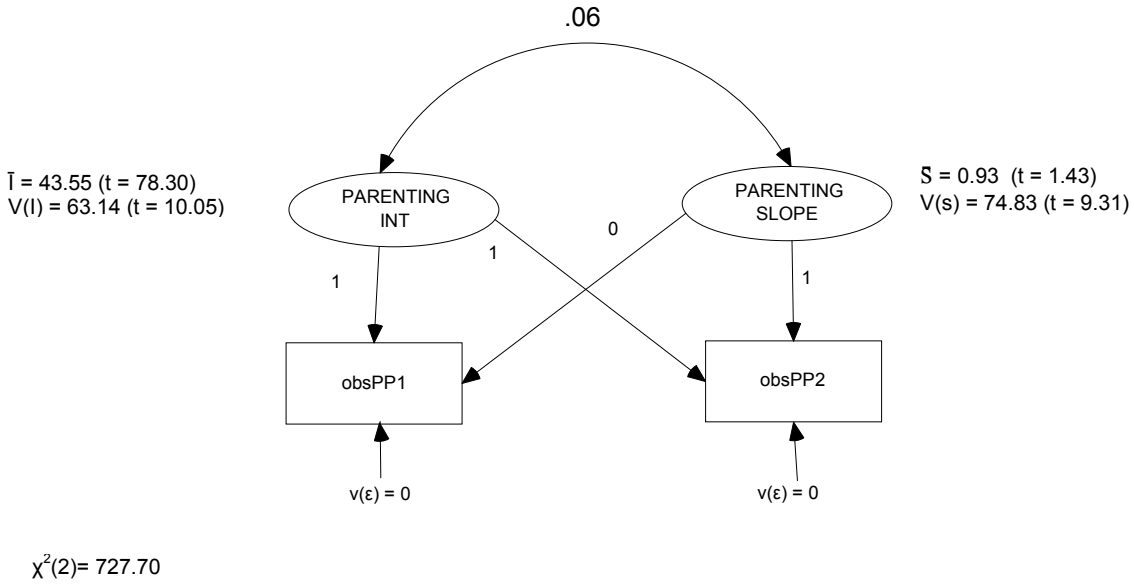


Figure 30. Univariate growth curve for parenting practices (waves 1-2).

The average intercept is $\bar{I} = 43.55$ with a variance of $V(I) = 63.14$. Both are significantly different from zero, as indicated by the *t* ratios of 78.30 and 10.05, respectively. In addition, there was an average increase in ineffective parenting as evidenced by the positive slope, but this was not statistically significant. In other words, there is no evidence for an increasing or decreasing trend. However, there is much variability in the slope, as evidenced by the significant *t* value of 9.31. The positive slope of ineffective parenting reflects the positive change from Time 1 to Time 2 in observer-ratings of ineffective parenting (see Table 10).

Table 10

Univariate Statistics for Observed Parenting Index Score

	N	Mean	SD	Variance
T1 Ineffective Parenting	203	43.53	7.95	63.17
T2 Ineffective Parenting	179	44.26	9.57	91.60

Because mental health and parenting practices change over time, the relationship between the two is best modeled as two related time-varying covariates. Consistent with the life course perspective, examining interlocking trajectories recognizes the mutual conjoint developmental processes that occur in the natural course of human development.

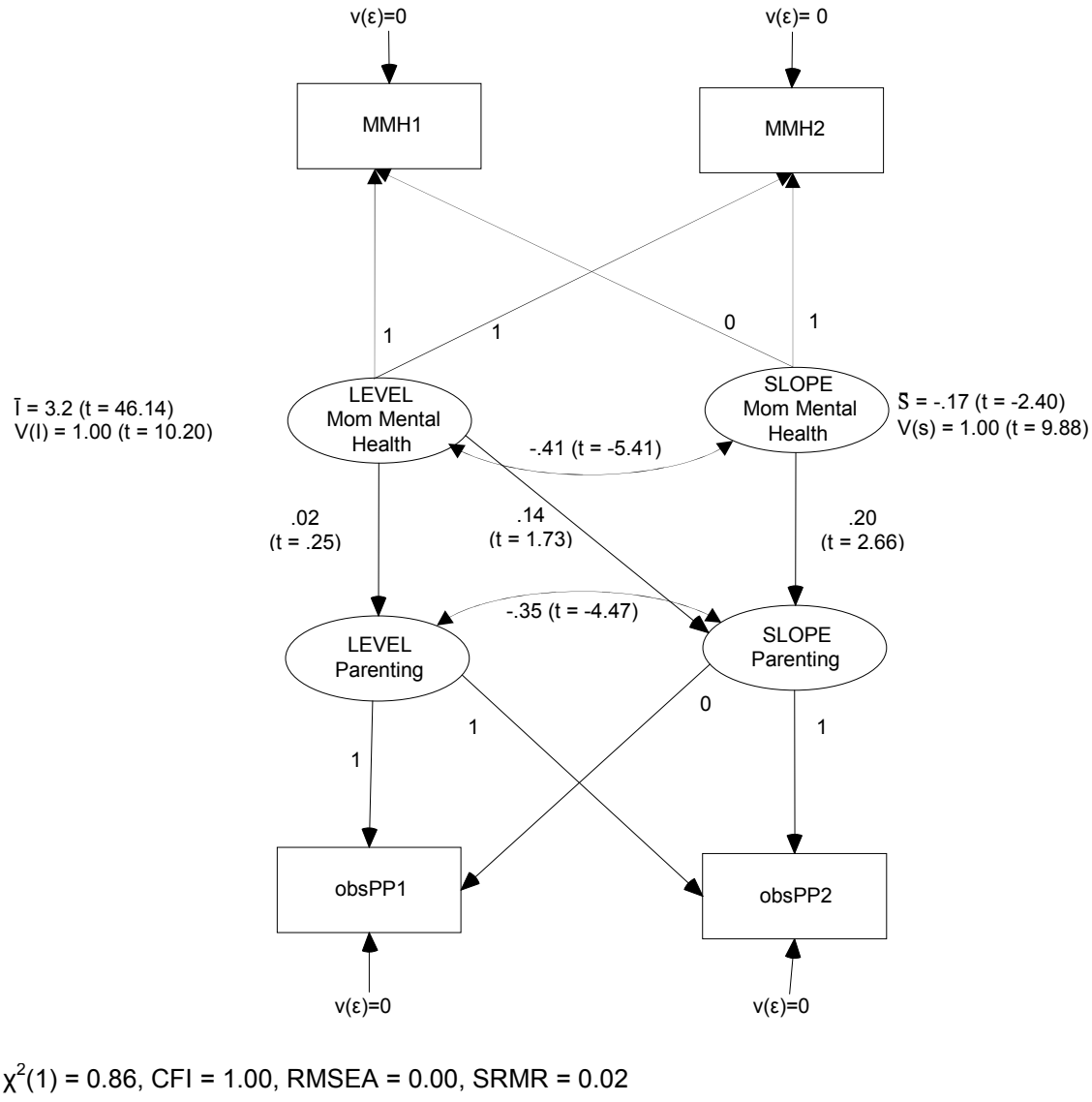


Figure 31. Interlocking trajectories of mothers' mental health and ineffective parenting (standardized coefficients).

This model takes into account the covariation of one process into the growth trajectory of another. To model the interlocking trajectories between mother's mental health and ineffective parenting, univariate growth curves are first estimated for each process separately (see Figures 29 and 30). After an adequate model is obtained, the two growth curve models are combined into a single model, with causal paths linking the two processes (see Figure 31). However, for the interlocking growth model, only the first two waves of mother's mental health were used since only the first two waves of ineffective parenting were available. Consistent with the overall theoretical model, level and change in mother's mental health were expected to influence level and change in parenting practices.

To achieve successful estimation of the model, the indicators of mother's mental health were summed to form an index score for each time point. These three index scores comprised the new indicator variables for the latent growth factors for mother's mental health. Furthermore, the residual error variances for the mental health indicators and the parenting practices indicators were fixed to zero.

The interlocking trajectories model showed non-significant effects from level of mother's mental health to level of ineffective parenting practices (.02, $t = .25$). Level of mother's mental health also did not have a significant effect on the slope of ineffective parenting (.14, $t = 1.73$). The greatest effect was from the slope of mother's mental health to slope of ineffective parenting (.20, $t = 2.66$). These results support the hypothesis that change in mother's poor mental health leads to ineffective parenting. Specifically, these results show that a positive magnitude change in poor mental health (i.e., a deterioration of mental health) leads to a positive magnitude change in ineffective parenting (i.e., deterioration of parenting

skills). In other words, the worse the mother's mental health gets, the worse her parenting becomes.

In the next set of analyses, the causal relationship between adolescent perceptions of parenting and adolescent mental health will be explored. In the full theoretical model, directional causal effects from parental mental health to ineffective parenting practices at Time 2 and from adolescent perceptions of parenting to adolescent mental health at Time 3 were assumed based on theoretical grounds, but measured within the same time period. Similar to the previous analyses exploring the relationship between mother's mental health and parenting practices, latent growth techniques such as auto-regressive, cross-lagged, and latent growth curve models, are used to explore the relationship between adolescent's perception of parenting and their mental health in greater detail.

The auto-regressive model for adolescent's perception of parenting across the three time periods shows high stability across time. To identify the model, the error variances and the loadings for each indicator were freely estimated and correlated with one another across the three waves of measurement. The stability coefficients from Wave 1 to Wave 2 and from Wave 2 to Wave 3 are .67 (t = 9.63) and .70 (t = 10.44) respectively, suggesting high stability (Figure 32).

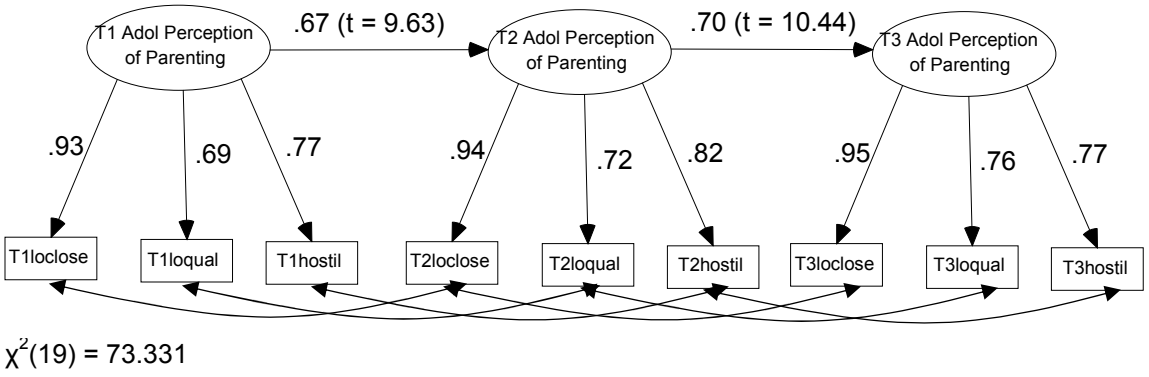


Figure 32. Autoregressive model for adolescent perception of parenting.

The auto-regressive model for adolescent mental health across the three time periods also shows high stability across time. To identify the model, the error variances and the loadings for each indicator were freely estimated and correlated with one another (not shown) across the three waves of measurement. The stability coefficients from Wave 1 to Wave 2 and from Wave 2 to Wave 3 are .56 (t = 7.86) and .63 (t = 8.64), respectively, suggesting high stability (Figure 33).

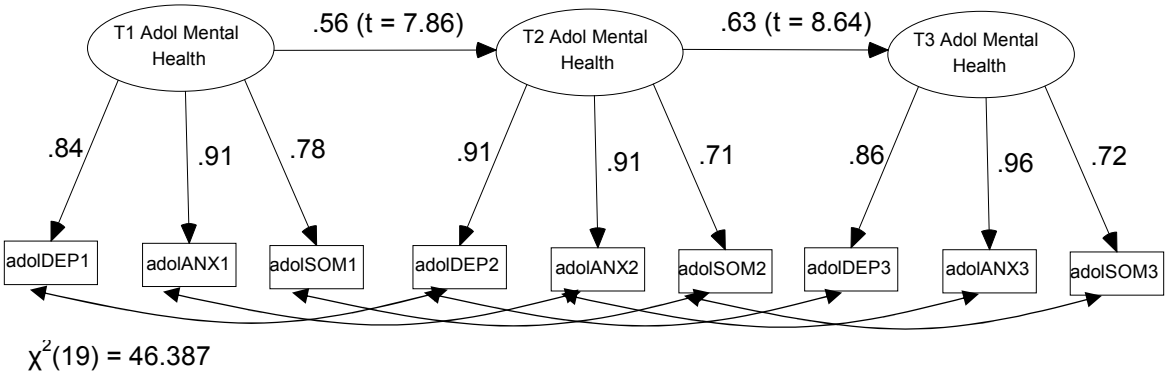


Figure 33. Autoregressive model for adolescent mental health (waves 1-3).

To model the cross-lagged effects of adolescent perception of parenting and adolescent mental health, the two auto-regressive models previously analyzed are combined into a single model (see Figure 34). The cross coefficients represent the effect of one latent variable at time *t* on change in the second attribute at the subsequent time point *t+1*, where change is reflected in the magnitude of the residual that remains after regressing each latent variable at time *t+1* on the immediate preceding latent variable at time *t*. Then the magnitudes of the cross coefficients can be compared to each other to gain insight into the extent to which the two variables reciprocate.

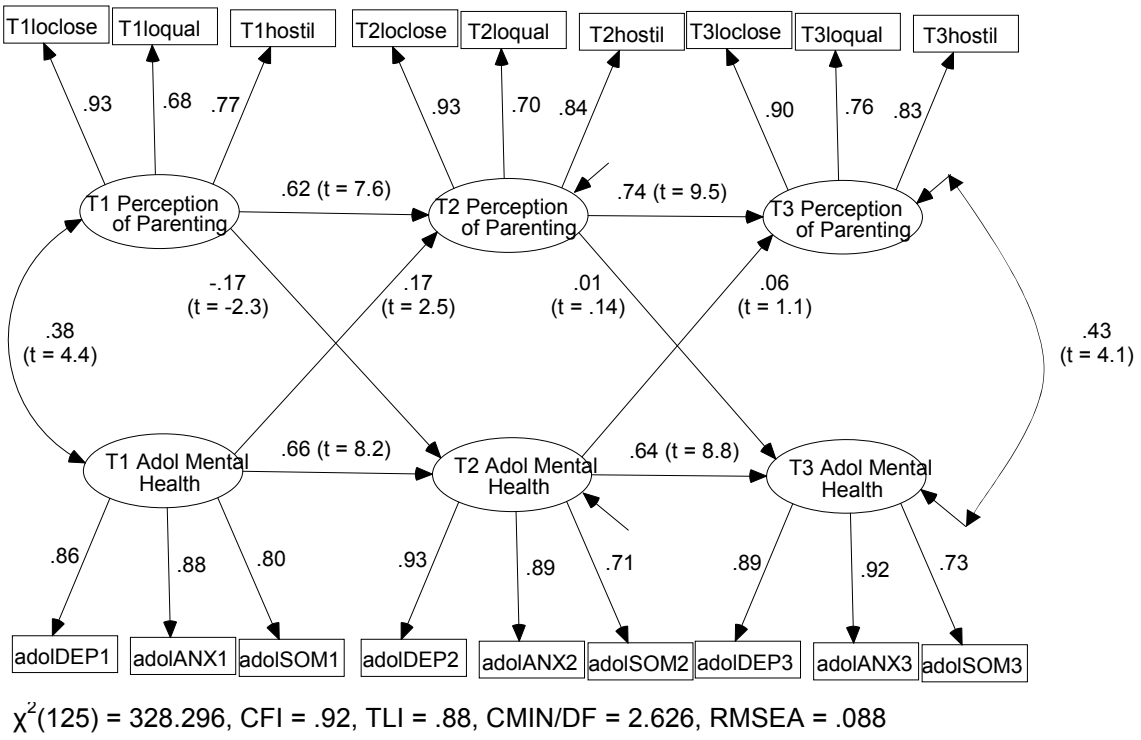


Figure 34. Cross-lagged model for perception of parenting and adolescent mental health.

The results of the cross-lagged model show significant cross coefficients from Time 1 to Time 2 only. Specifically, Time 1 perception of parenting significantly predicted Time 2 adolescent mental health. However, contrary to expected, the effect was negative ($\hat{\beta}$ = -.17, *t* = -2.3), suggesting that an increase in the perception of ineffective parenting results in a negative change in poor adolescent mental health. The coefficient is in the opposite direction than what was expected, however this kind of counter-intuitive results are not rare and have been found in previous studies using cross-lagged designs (cf. Lorenz et al., 2004). One possible reason for this counter-intuitive coefficient is that individuals experience variability in mental health, so that extremely high levels at time *t* are not likely to be as high at time *t* +1, although they may still be relatively high. As a result, we may be observing a "restoration to more normal baseline levels" accounted for by the relative improvement in emotional

well-being (Lorenz et al., 2004). In fact, an observation of the univariate descriptive statistics for each indicators for perception of parenting (Table 10) and adolescent mental heath (Table 11), did not show uniform variability; rather the indicators show a mixed trend of increasing and decreasing mean levels across the three waves of measurement.

The cross coefficient from Time 1 adolescent mental health to Time 2 perception of parenting was also significant ($\hat{\beta}$ = .17, t = 2.5), suggesting that an increase in mean levels of poor mental health of adolescents leads to a subsequent increase in the adolescent's perception of parenting ineffectiveness. These results may suggest that a diminished mental health among adolescents negatively biases their perception of their parent's parenting practices.

An examination of the contemporaneous model (see Figure 35) supports the notion of a reciprocal effect between adolescent's perception of parenting and adolescent mental health. Again, a significant negative effect of adolescent's perception of parenting on adolescent mental health was observed ($\hat{\beta}$ = -.22, t = -2.1) and a significant effect of adolescent mental health on perception of parenting was observed ($\hat{\beta}$ = .31, t = 3.8). However, these significant reciprocal effects are not observed in Time 3. The results of the contemporaneous model are consistent with the cross-lagged model.

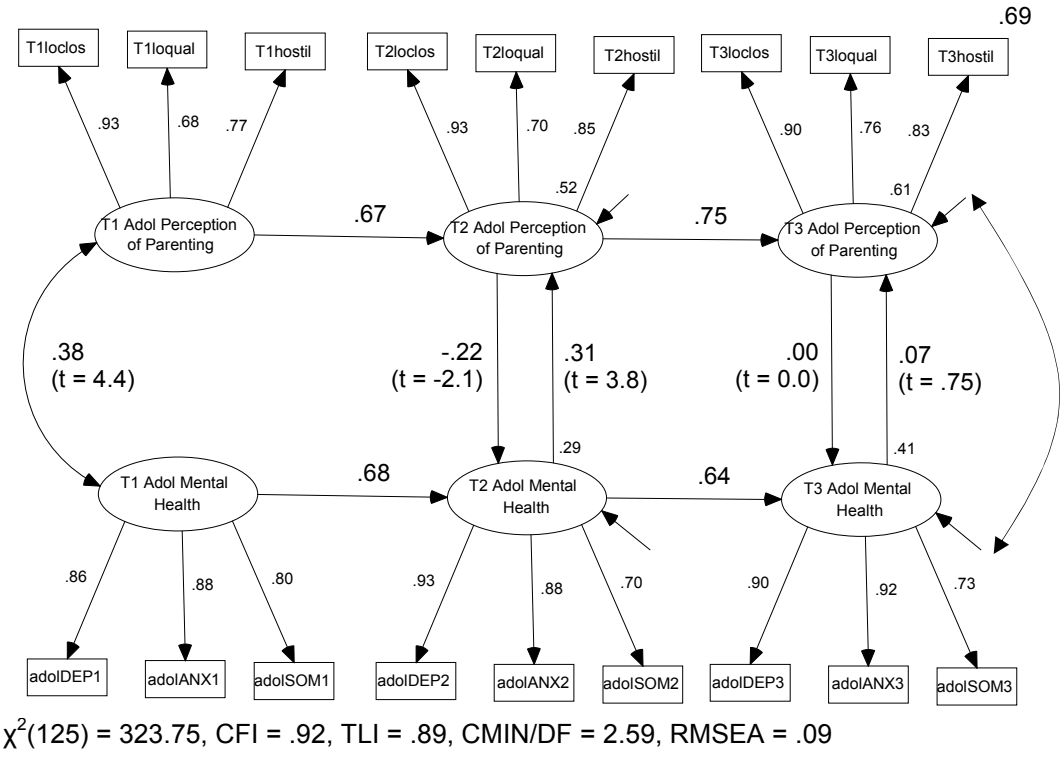


Figure 35. Contemporaneous model for perception of parenting and adolescent mental health.

The contemporaneous path from adolescent mental health to adolescent's perception of ineffective parenting addresses the methodological concern that the adolescents' ability to recall events of poor parenting may be affected by their psychological state at the time the data were collected. Adolescents with poor mental health may be more likely to recall negative examples of poor parenting from their mothers.

Again, a counter-intuitive coefficient is observed in the path from perception of parenting to mental health. This coefficient is in the opposite direction than what was expected, however as observed in the cross-lagged model, this kind of counter-intuitive results are not rare and have been found in previous studies (cf. Lorenz et al., 2004).

The models thus far examined the effects of time-invariant covariates on patterns of intra-respondent change in a time-varying attribute. As illustrated in the analyses, a limitation

of the autoregressive and cross-lagged models is that it measures residual change and not mean-level change. Variables can be highly stable across time, but it does not necessarily give any information about direction of change—increasing or decreasing mean levels—and pattern (linear slope, quadratic slope, etc.) of change. Also, as just observed, cross-lagged and contemporaneous models can result in counter-intuitive coefficients that may be the result of an artifact of the data rather than offering any significant insight into the theoretical model. Latent growth curve models address the weaknesses of these approaches examined thus far and will be explored next.

In the next section, latent growth curve models are used to examined the effects of a second time-varying covariate. In terms of a human development framework, this approach allows one to examine the longitudinal covariation of one family member's change in behavior or feelings with the changes in the same behaviors and feelings of another. To estimate interlocking trajectories between mothers' mental health and her parenting practices, univariate growth curve models for mental health (Figure 29) and parenting practices are estimated separately first.

To model the univariate growth curve model for perception of parenting, a linear growth model for continuous outcomes as shown in Figure 36 was estimated by maximum likelihood estimation using Mplus. Because of the significant increase in the number of parameters for a second-order growth curve model, index scores were used as the indicators for the three waves of measurement. The index score for each wave was created by taking the mean of the three indicators: low quality, low closeness, and hostility. The results of the univariate growth analysis show significant mean estimate for the intercept term (t = 57.35), but non-significant estimate for the slope term (t = .46). Significant variances in intercept (t =

5.33) and slope (t = 2.22) of perception of parenting were also observed. Given the significant variance in slope, the model is appropriate for further analysis using latent class growth analysis or general mixture modeling.

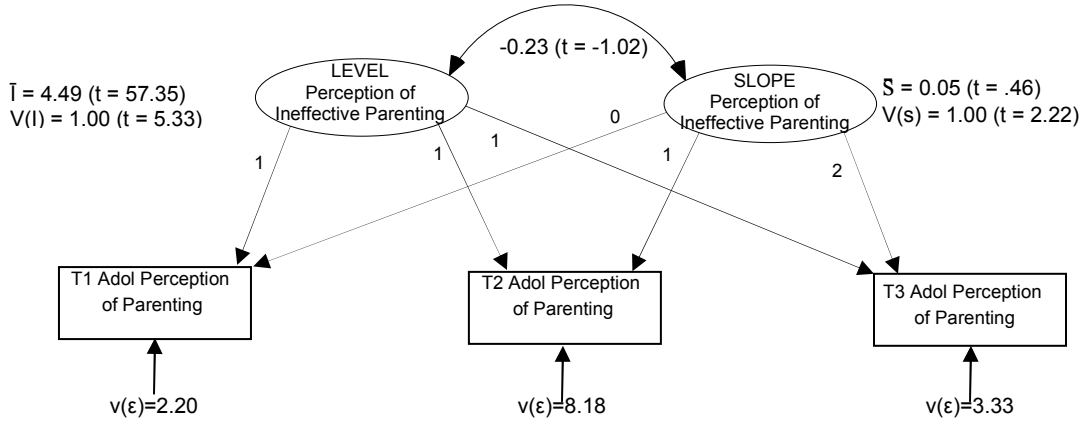


Figure 36. Univariate growth curve for adolescent perception of parenting (standardized coefficients).

Table 11 summarizes the results of the univariate statistics for the variables comprising the three indicators of adolescent mental health.

Table 11

Univariate Statistics for Adolescent's Perception of Parenting Index Variables

	N	Mean	SD	Variance
T1 Perception of Parenting	210	14.36	3.51	12.30
T2 Perception of Parenting	210	13.64	4.20	17.67
T3 Perception of Parenting	210	14.55	4.14	17.11

To model the univariate growth curve model for adolescent mental health, a linear growth model for continuous outcomes as shown in Figure 37 was estimated by maximum likelihood estimation using Mplus. To achieve successful estimation, the residual error variances were freely estimated. Because of the significant increase in the number of

parameters for a second-order growth curve model, index scores were used as the indicators for the three waves of measurement. The results of the univariate growth analysis show significant mean estimates for the intercept term (t = 47.19), but not the slope term (t = -.53). Significant variances in intercept (t = 5.43) and slope (t = 3.11) of adolescent mental health were also observed. Given the significant variance in slope, the model is appropriate for further analysis using latent class growth analysis or general mixture modeling.

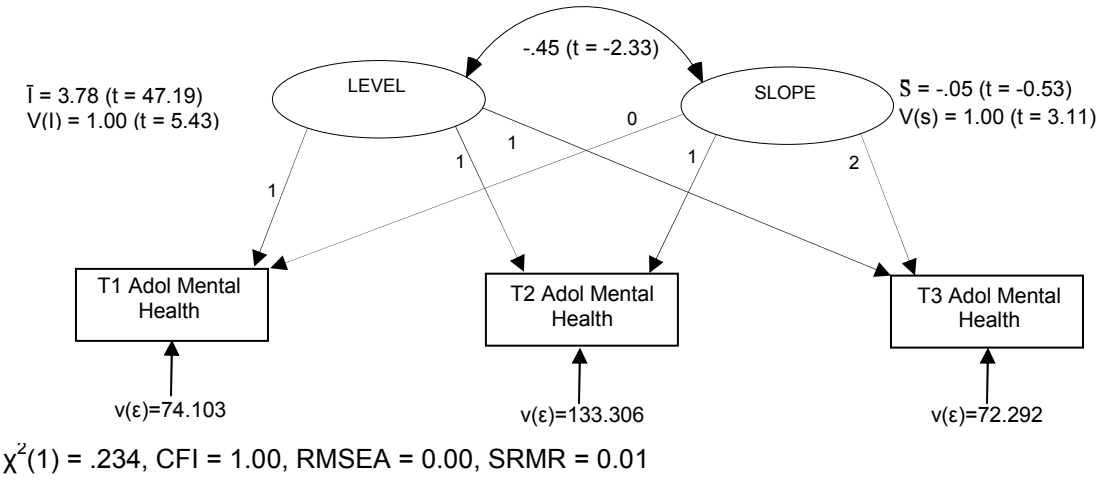


Figure 37. Univariate growth curve model for adolescent mental health (standardized coefficients).

The high CFI value of 1.00 combined with a low SRMR values of .05 and .01 for perception of ineffective parenting and adolescent mental health, respectively suggest an excellent model fit. There is slight decline in adolescent mental health over time as evidenced by the negative slope, but it is not significant ($\hat{\beta}$ = -.05, t = -.53). Table 12 summarizes the results of the univariate statistics for the three indicators of adolescent mental health.

Table 12

Univariate Statistics for Adolescent Mental Health Index Variables

	N	Mean	SD	Variance
T1 Adolescent Mental Health	210	53.65	16.65	277.37
T2 Adolescent Mental Health	210	52.82	16.92	286.41
T3 Adolescent Mental Health	210	52.94	17.23	296.98

Because the trajectories of perception of parenting practices and adolescent mental health change over time, the relationship between the two is best modeled as two related time-varying covariates. Consistent with the life course perspective, examining interlocking trajectories recognizes the mutual conjoint developmental processes that occur in the natural course of human development. This model takes into account the covariation of one process into the growth trajectory of another. To model the interlocking trajectories between adolescent's perception of parenting and adolescent mental health, univariate growth curves are first estimated for each process separately (see Figures 36 and 37). After an adequate model is obtained, the two growth curve models are combined into a single model, with causal paths linking the two processes (see Figure 38). Consistent with the overall theoretical model, level and change in perception of parenting are expected to influence level and change in adolescent mental health.

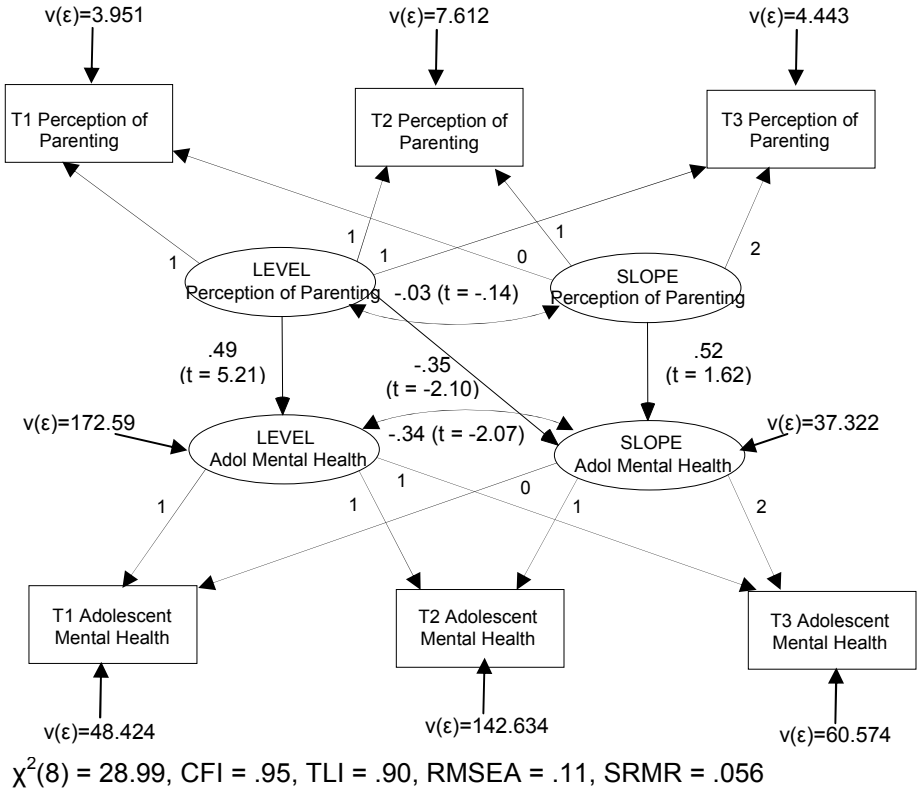


Figure 38. Interlocking trajectories model for adolecent's perception of parenting and adolescent mental health (standardized coefficients).

Because of the considerable increase in the number of parameters in the combined model and to facilitate successful estimation of the model parameters, the indicators for adolescent's perception of parenting and adolescent mental health were summed to form an index score for each time point. These three index scores comprised the new indicator variables for the latent growth factors for adolescent's perception of parenting and adolescent mental health. Consistent with the univariate growth curve models for both growth processes, the residual error variances were freely estimated.

The interlocking trajectories model showed a significant effect from level of adolescent's perception of parenting to level of adolescent mental health. Level of perception of parenting significantly predicted the level of adolescent mental health ($\hat{\beta}$ = .49, t = 5.21)

and also the slope of adolescent mental health ($\hat{\beta}$ = -.35, t = -2.10). The slope of perception of parenting did not significantly predict slope of adolescent mental health ($\hat{\beta}$ = .52, t = 1.62). Further analyses of the reciprocal effects (paths not shown) showed that level of mental health significantly predicted level of perception of ineffective parenting ($\hat{\beta}$ = .49, t = 4.99). Also, both level ($\hat{\beta}$ = .62, t = 4.40) and slope ($\hat{\beta}$ = .54, t = 3.19) of adolescent mental health predicted slope of perception of ineffective parenting. These results are consistent with the results of the cross-lagged (Figure 34) and contemporaneous (Figure 35) models. These earlier models also showed evidence for causal and contemporaneous reciprocal relationship between adolescent's perception of parenting and adolescent mental health.

Latent Class Growth Analysis

Recent advances in methodological approaches and statistical software address the aforementioned limitations of traditional regression, autoregressive, and LGC approaches. Latent variable modeling software such as Mplus offers various modeling options that handle non-normality of data, discrete variables, and mixed modeling approaches. As Muthén and Muthén (2000) aptly put it, commonly used statistical approaches such as regression analysis, factor analysis, and structural equation modeling take a variable-centered approach to data analysis. Whereas studies using heterogeneous groups of individuals, as often the case with alcohol, drug, and mental health research studies, require person-centered approaches, such as cluster analysis, finite mixture analysis, latent class analysis (LCA), latent transition analysis (LTA), latent class growth analysis (LCGA), growth mixture modeling (GMM), and general growth mixture modeling (GGMM).

Conceptually, LCA is similar to cluster analysis (i.e., multivariate mixture estimation) in the sense that it is used to uncover groups or types of cases based on observed data and then assign individual cases to these latent groups. LCA is also similar to factor analysis in the sense that they are both data reduction techniques. However, the difference is that factor analysis is concerned with the structure of variables (i.e., correlations among variables), whereas LCA is more concerned with the structures of cases (i.e., classification of individuals). While there is clearly some connection between these two issues, LCA does seem more strongly related to cluster analysis than to factor analysis (Macmillan & Copher, 2005).

The hallmark of latent class analysis is the ability to capture previously unobserved subpopulation distributions within a larger heterogeneity of population distribution. In this sense, LCA is a form of mixture modeling, which refers to modeling with categorical latent variables that represent subpopulations where population membership is not known but is inferred from the data. Specifically, this is referred to as "finite mixture modeling" in statistics (McLachlan & Peel, 2000). Figures 39, 40, and 41 show the marked heterogeneity of growth trajectories for the observed individual values for the three indicators of adolescent mental health—depression, anxiety, and somatic symptoms. To model this heterogeneity of growth trajectories, a type of latent class analysis, called latent class growth analysis (LCGA) is used.

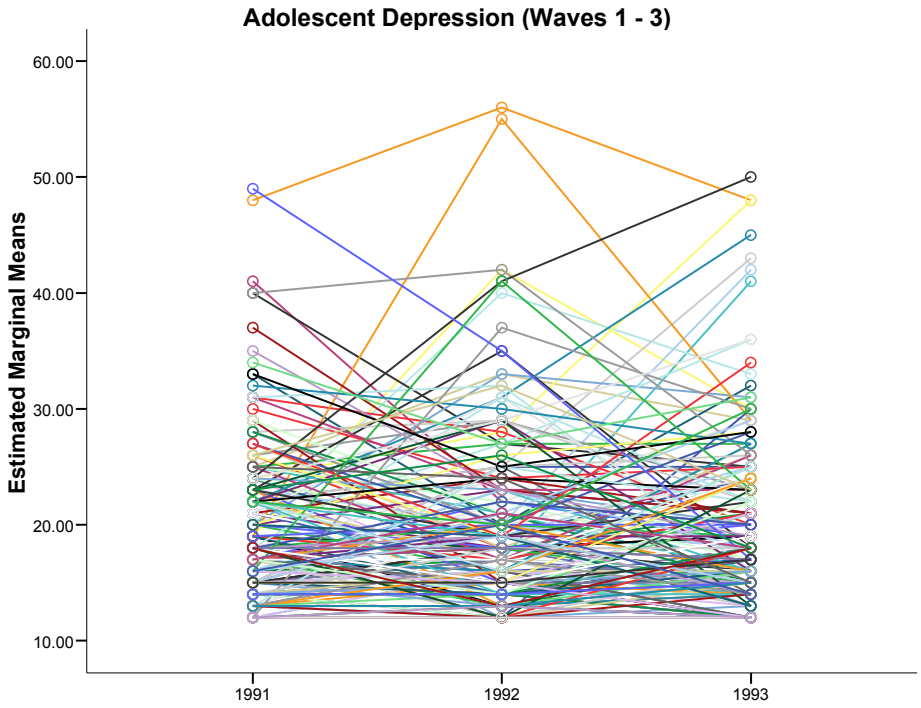


Figure 39. Observed individual values for adolescent depression.

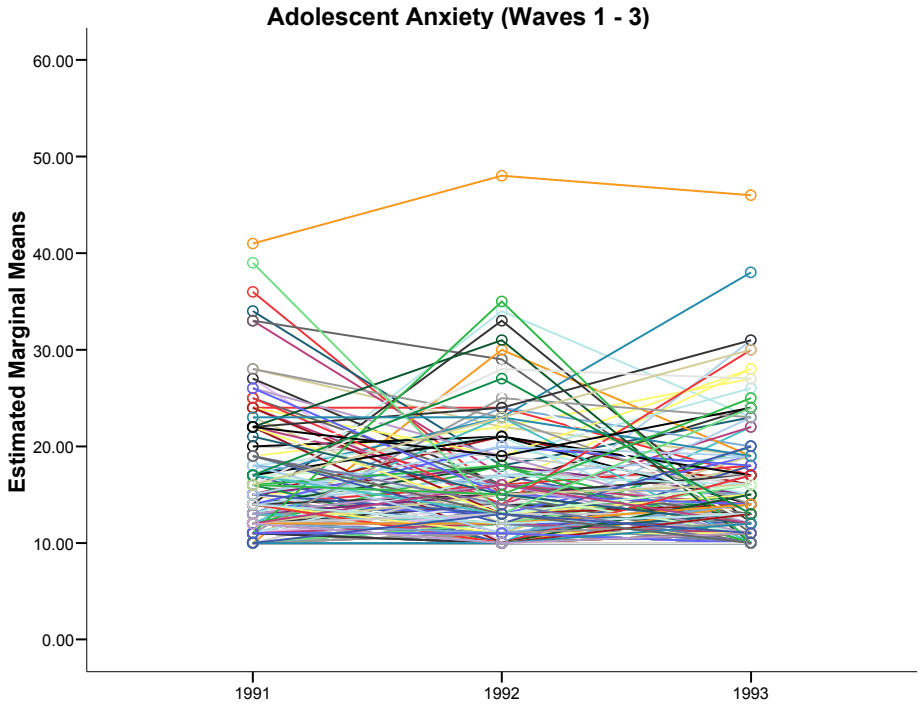


Figure 40. Observed individual values for adolescent anxiety.

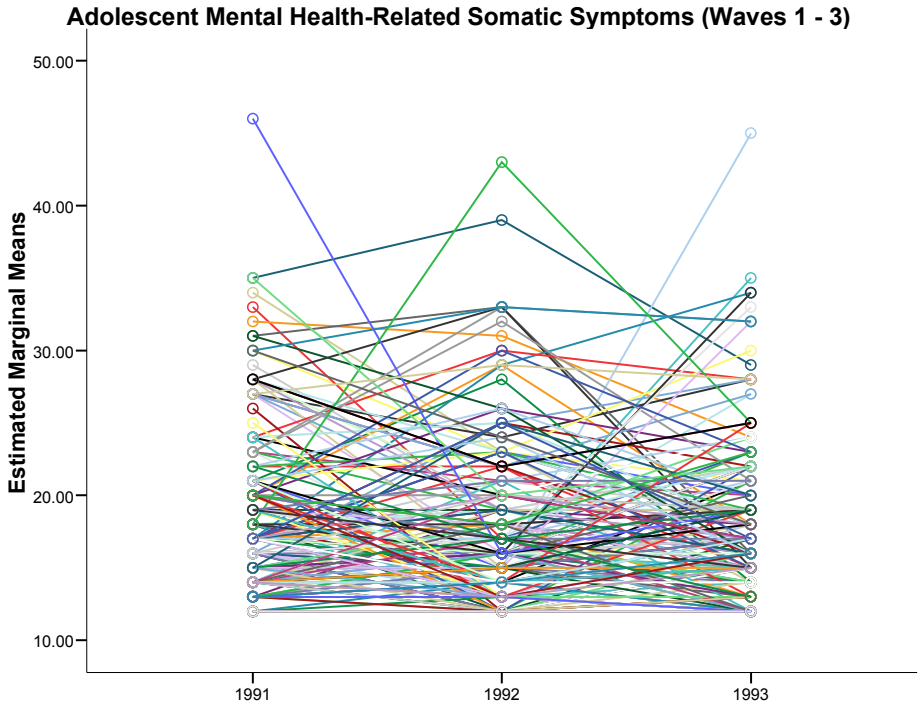


Figure 41. Observed individual values for adolescent mental health-related somatic symptoms.

As for assessing model fit, LCA employs many of the same model fit criterion as structural equation modeling, including BIC (Bayes information criterion), AIC (Aikaike information criterion) and CAIC (Consistent AIC, which penalizes for sample size as well as model complexity). These are goodness of fit measures which take into account model parsimony (that is, it penalizes for number of parameters in relation to maximum possible number of parameters). The lower the BIC, AIC or CAIC values, the better the model in comparison with another. Existing studies using LCA have frequently use BIC, with the best fitting model having the lowest BIC (cf. Guo, Wall, & Amemiya, 2006), and so will be used for the present analyses.

In mixture modeling with longitudinal data, unobserved heterogeneity in the development of an outcome over time is captured by categorical and continuous latent

variables. The simplest longitudinal mixture model is latent class growth analysis (LCGA). In LCGA, the mixture corresponds to different latent trajectory classes. No variation across individuals is allowed within classes (Nagin, 1999; Roeder, Lynch, & Nagin, 1999). Another longitudinal mixture model is the growth mixture model (GMM). In GMM, within-class variation is allowed for the latent trajectory classes. The within-class variation is represented by random effects, that is, continuous latent variables, as in regular growth modeling (Muthén & Shedden, 1999; Muthén et al., 2002). Using structural equation modeling in Mplus, LCGA and GMM can be modeled as follows:

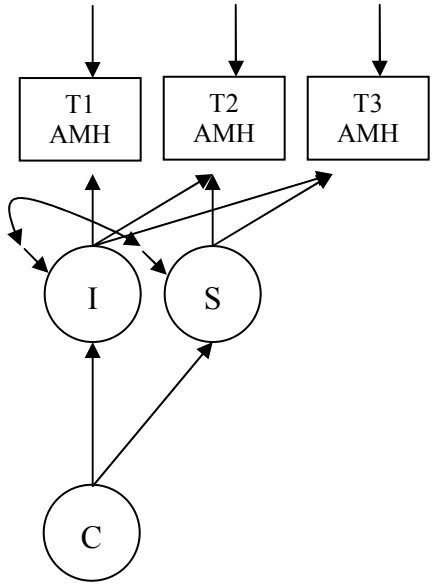


Figure 42. Latent class growth analysis for adolescent mental health.

where *c* is the categorical latent variable, with growth factors *i* and *s*, for intercept and slope respectively. The arrows from *c* to the growth factors *i* and *s* indicate that the intercepts of the regressions of the growth factors on *x* vary across the classes of *c*. This corresponds to the regressions of *i* and *s* on a set of dummy variables representing the categories of *c*. The arrow from *x* to *c* represents the multinomial logistic regression of *c* on *x*. For the present analysis, LCGA will be used instead of GMM since the purpose is primarily exploratory (i.e., to

identify classes), rather than to estimate within class parameters with precision. Conducting initial exploratory latent class analyses using LCGA instead of GMM also puts less computational burden on the software, allowing for faster convergence. Once a satisfactory number of classes are established using various fit indices, the next step is to conduct GMM to improve model fit and to estimate within class parameters with greater precision.

The unique contribution of latent class growth modeling over latent growth curve modeling is that latent growth curves estimates the mean trajectories for the whole population (fixed effect) and estimates the individual variation about the grand mean as observed by the variance of the growth factors (random effects). However, as evidenced by the univariate plots for the observed individual growth trajectories for the depression, anxiety, and somatic symptoms, there is marked heterogeneity and it is possible that there are certain "types" or "classes" of growth patterns. These patterns can be characterized by their own mean trajectories and variances. Hence, while latent growth curves are useful for assessing change over time, it does not model the heterogeneity that corresponds to qualitatively different patterns of development. Therefore, to explore growth heterogeneity and to identify different profiles of longitudinal mental health changes, latent class growth analysis (LCGA) was used.

To begin exploring the latent class growth trajectories for adolescent mental health, a linear latent growth model was estimated using the index scores as indicators for the three waves of measurement (see Figure 43).

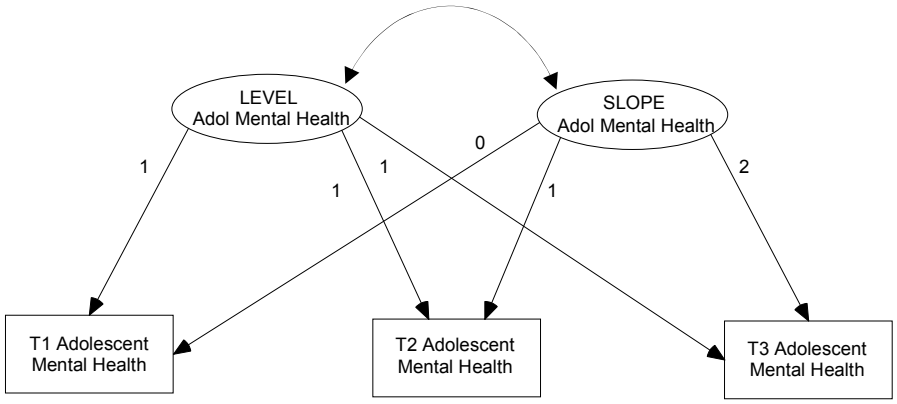


Figure 43. Univariate latent growth model for adolescent mental health.

Once this model had been satisfactorily estimated, an unconditional latent class growth model is specified by adding a categorical latent class variable to the model as follows:

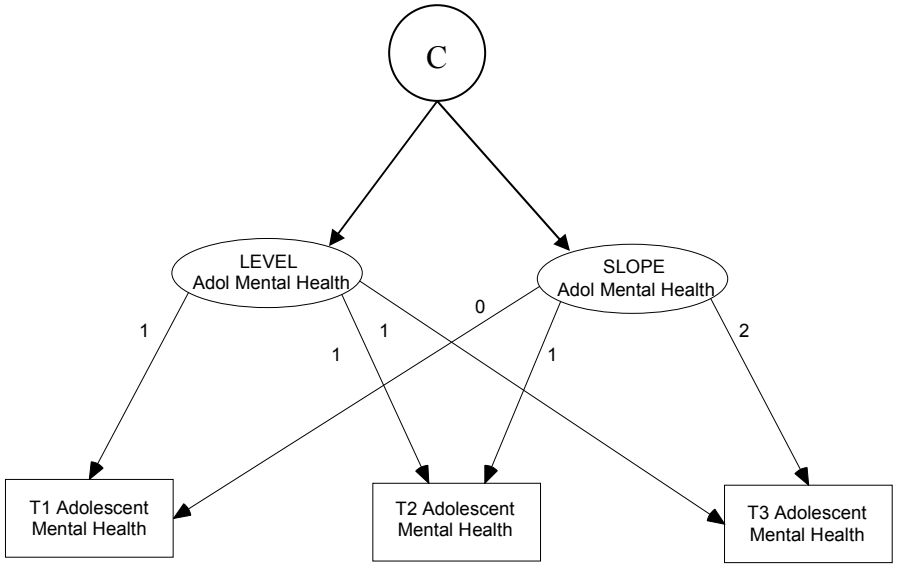


Figure 44. Latent class growth analysis model for adolescent mental health.

As required by LCGA, the variances of the growth factors are fixed to zero, allowing no within group variation. Also, the covariance of the growth factors are contrained to zero. This follows from the variance restriction necessary to estimate distinct trajectories. The intercept

is set at Time 1 measurement of adolescent mental health (Year 1991, mean age of adolescent child = 14.33).

To determine the number of latent classes that best capture the underlying patterns of mental health growth trajectories, a series of latent class growth models are specified whereby one additional class is added to each successive model. The model testing began with a single class model and continued until the addition of a new class resulted in non-convergence. Six classes were evaluated, with only the one-, two-, and three-class models converging successfully. However, BIC values were obtained for six classes for comparative purposes (see Figure 45).

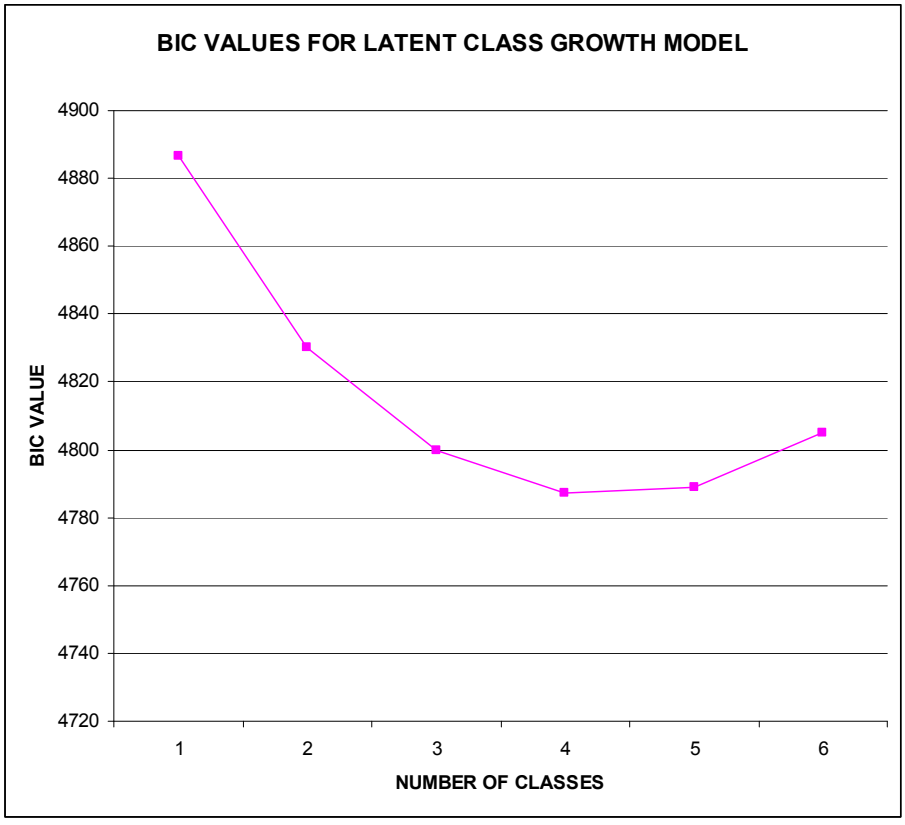


Figure 45. BIC values for latent class growth model.

A low BIC value indicates a better fitting model. Although the four-class model appears to be the best fit based on BIC value alone, it did not successfully converge. The

four-, five-, and six-class models resulted in classes with only a single case within a class. Since these models resulted in a less than 1% class membership solution, these solutions are meaningless and do not offer any substantial insight or interpretation into the data. Therefore, the next best model fit based on BIC values and interpretability of results was chosen. According to this criterion, the three-class model best fit the data.

In addition to looking for the lowest BIC value, there are other indicators of good model fit given in the Mplus output. One of these is the posterior probability table (see Table 13). This table tells you how successful the classification scheme is. High numbers (> .90) along the diagonal and smaller numbers elsewhere gives evidence for a good solution.

Table 13

Average Latent Class Probabilities for Most Likely Latent Class Membership (Row) by Latent Class (Column)

		Actual Class		
		1	2	3
Predicted Class	1	0.975	0.012	0.014
	2	0.055	0.941	0.003
	3	0.030	0.000	0.970

The posterior probabilities are quite high—.975, .941, .970—suggesting that the predicted class memberships are matching the actual class memberships, hence a good model fit and a satisfactory latent class solution. The estimated class trajectories for the three-class solution are shown in Figure 46. The graph of the estimated means show three clearly distinct patterns of longitudinal change in adolescent mental health trajectories: (1) a chronically-low symptoms or “healthy” group (81.6%); (2) a recovery or “getting healthier” group (13.1%);

and (3) a deteriorating or "getting worse" group (5.3%). The final class count and proportions for the three-class solution are shown in Table 14.

Table 14

Final Class Counts and Proportions for the Three-Class Growth Model

Class	Count	Proportion
1	174	0.82
2	27	0.13
3	9	0.05

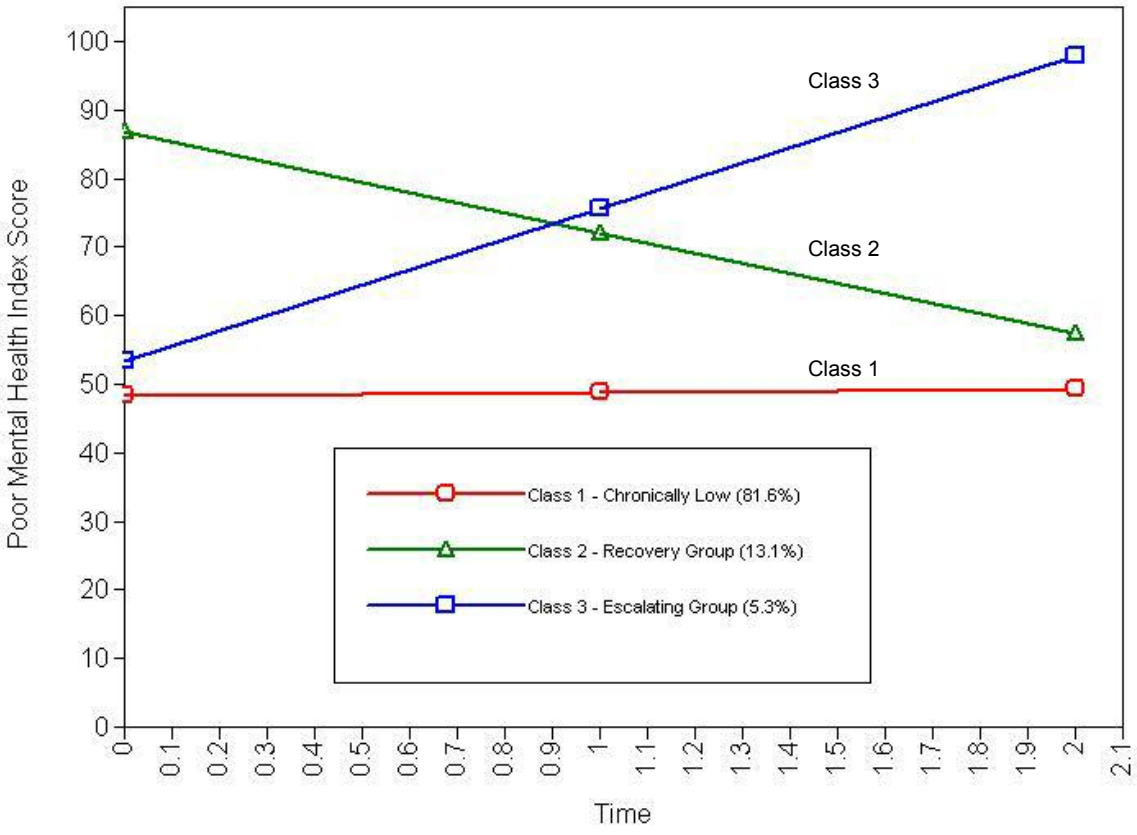


Figure 46. Estimated mean trajectories for the three-class latent class growth model.

The mean estimates shown in Figure 46 appear to adequately summarize the heterogeneity of individual trajectories in the dataset (see Figure 47). In Figures 48 to 50, the individual trajectories are separated by the three classes. What is evident in the graphs is that there are many trajectories that show a quadratic trend, i.e., an increase from Time 1 to Time 2, then a subsequent decrease from Time 2 to Time 3. Perhaps respecifying the underlying univariate growth curve to include a quadratic term could capture this trajectory pattern. In the present analysis, these trajectories were estimated using a linear change model.

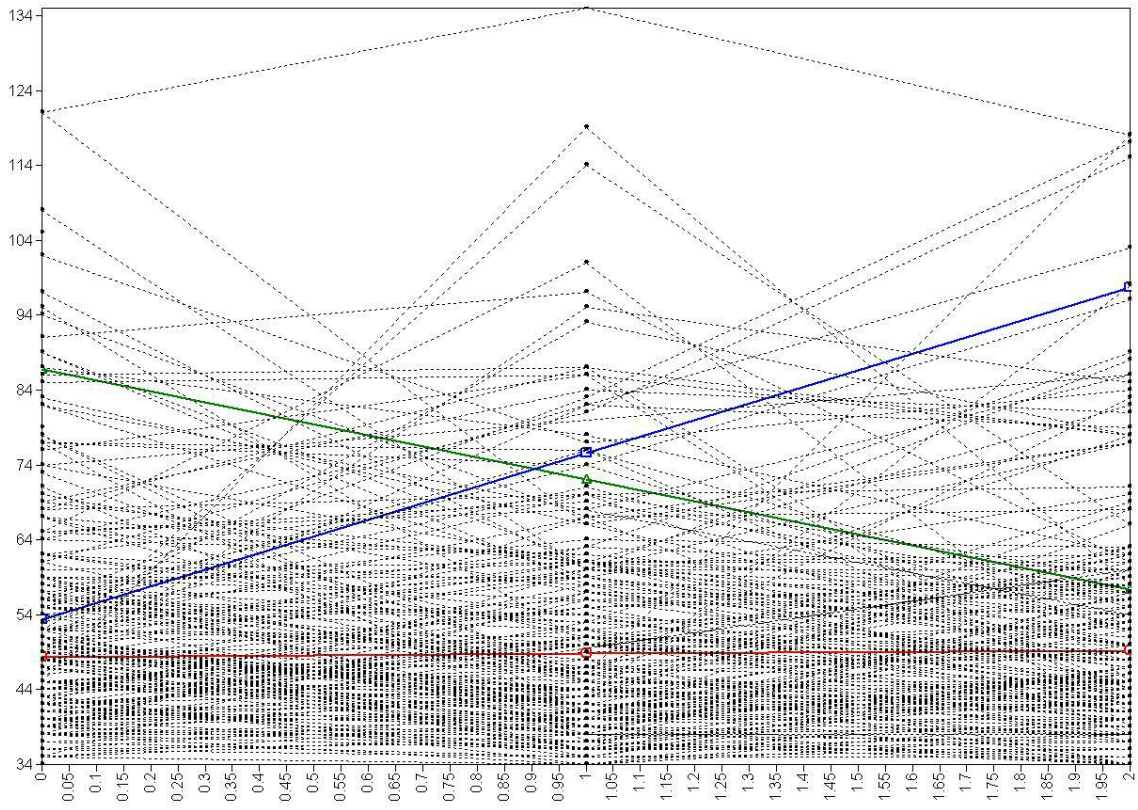


Figure 47. Observed individual values with estimated means.

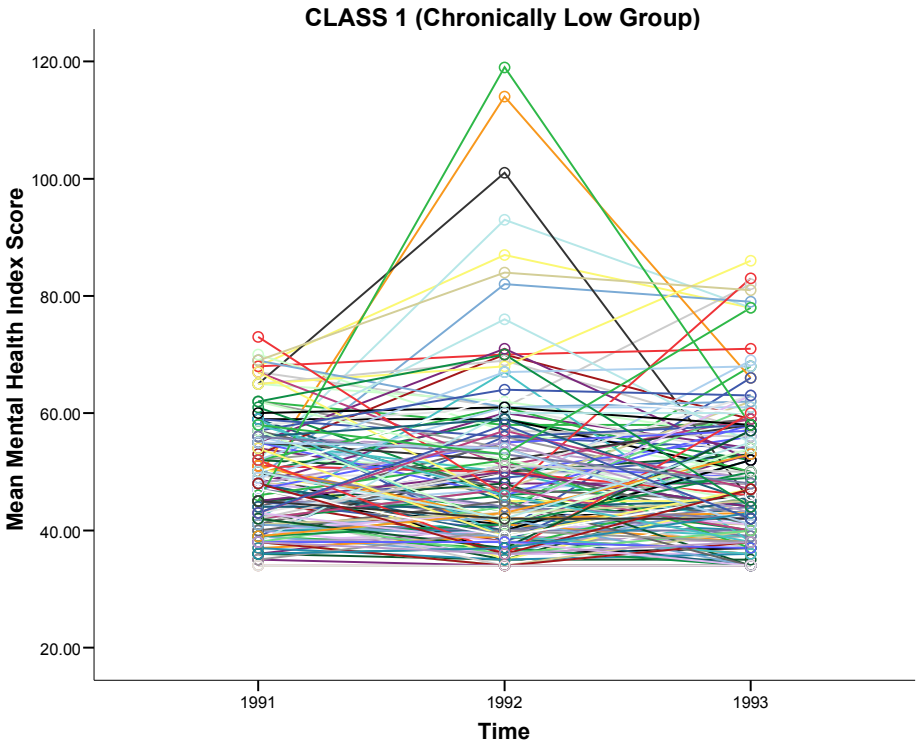


Figure 48. Individual trajectories for class 1 (chronically low group).

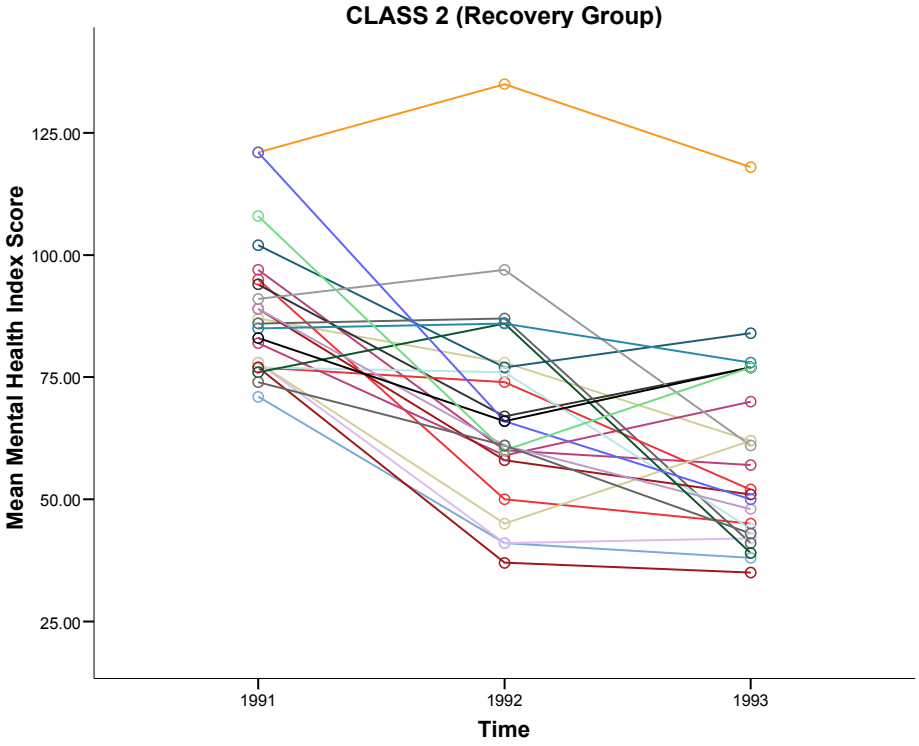


Figure 49. Individual trajectories for class 2 (recovery group).

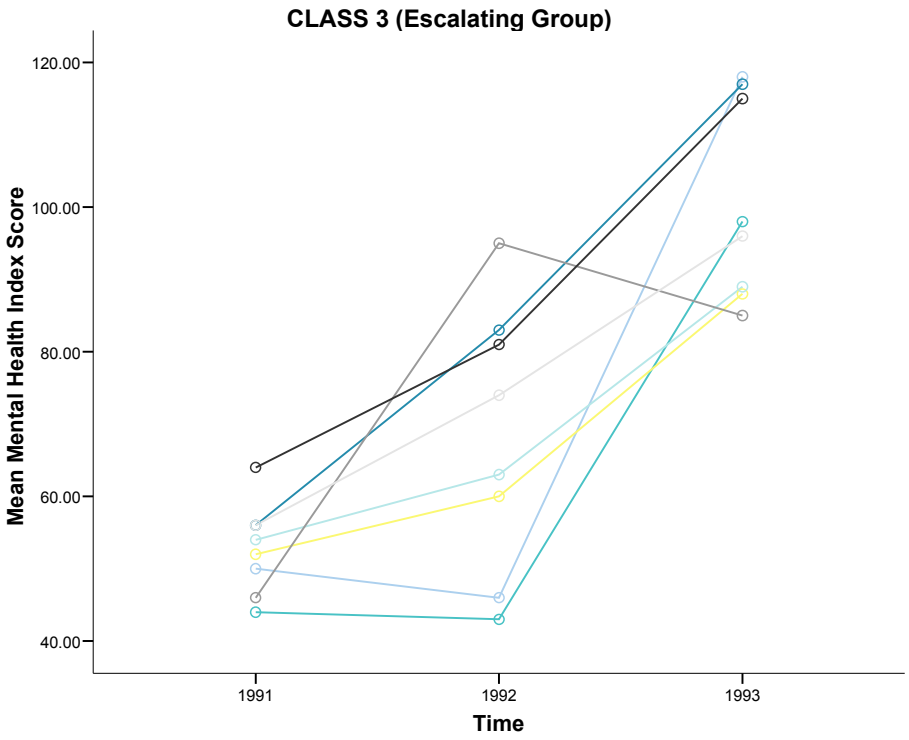


Figure 50. Individual trajectories for class 3 (escalating group).

The estimates of means and variances for the intercepts and slopes for each of the classes are shown in Table 15. Class 1 represented a group of adolescents who are relatively healthy for the most part during their teenage years, ages 14 to 16 (Year 1991 to 1993). The mental health statuses of these adolescents are very stable and report consistently little or no symptoms of depression, anxiety or somatic symptoms. Class 2 represented a group of adolescents who reported high levels of poor mental health symptoms early in their adolescence, but gradually improved and reported fewer and fewer symptoms of poor mental health from 1991 to 1993. These adolescents can be labeled as the "recovery group". By the age of 16 or so, these adolescents are reporting almost as good mental health status as those in Class 1. Class 3 adolescents are those who started by reporting relatively low symptoms of

poor mental health, similar to the level of Class 1 adolescents, but continued to report more and more symptoms of depression, anxiety, and somatic symptoms, giving evidence of deteriorating mental health.

Table 15

Growth Parameter Estimates for Each Latent Class

Class	Parameter	Estimates	S.E.	Est./S.E.
Class 1				
	Means			
	I	48.33	0.92	52.65
	S	0.45	0.51	0.87
	Variances			
	I	70.30	29.44	2.39
	S	15.05	17.31	0.87
Class 2				
	Means			
	I	86.72	3.66	23.67
	S	-14.69	1.72	-8.56
	Variances			
	I	70.30	29.44	2.39
	S	15.05	17.31	0.87
Class 3				
	Means			
	I	53.40	2.46	21.73
	S	22.16	3.71	5.97
	Variances			
	I	70.30	29.44	2.39
	S	15.05	17.31	0.87

With the class membership information, the subjects were cross-checked for between-group differences in terms of their reported values on the Time 1 socioeconomic stressors variables (see Table 16). There were several interesting findings. First, it appears that females are over-represented in Class 3—the escalating poor mental health class. This finding warrants further exploration into gender differences. However, Class 3 individuals also reported higher mean levels of spousal support and even higher levels of social support than

those in Class 2 (recovery group), to which may be attributed the overall lower mean level of poor mental health at Time 1. Also as expected, those in the escalating poor mental health group (Class 3) also reported higher mean levels of negative life events and economic stress than the other two groups at Time 1. But, surprisingly, Class 3 individuals also reported the lowest level of work stress.

Table 16

Class Differences in Mean Estimates of Time 1 Socioeconomic Contextual Stressors

	Class	Mean	SD
Sex	1	.48	.50
(0 = female)	2	.48	.51
(1 = male)	3	.22	.44
Spousal Support	1	96.47	53.89
	2	89.19	55.99
	3	101.89	69.09
Social Support	1	59.42	7.07
	2	55.26	8.69
	3	58.56	8.22
Negative Life Events	1	2.04	2.14
	2	1.59	1.42
	3	2.67	2.55
Economic Stress	1	51.13	9.66
	2	52.74	8.65
	3	55.11	10.42
Work Stress	1	55.80	11.28
	2	54.43	10.55
	3	52.00	12.46

Class: 1=Chronically Low, 2=Recovery, 3=Escalating

An analysis of variance was conducted to test for groups differences in mean levels of Time 1 socioeconomic contextual stressors (see Table 16). The ANOVA results showed that

the three classes differed significantly only in terms of their social support, $F(2, 207) = 3.76$, $p = .02$. Considering unequal cell sizes with equal variances, as evidenced by a non-significant Levene's Test, post-hoc analysis with Hochberg's GT2 adjustment revealed that Class 1 and Class 2 differed significantly in their mean levels of social support ($M_{1-2} = 4.16$, $SE = 1.52$, $p = .02$). The lack of significant mean differences with Class 3 may be due to its small sample size ($N = 9$).

Table 17

Analysis of Variance for Class Differences on Time 1 Socioeconomic Contextual Stressors

	SS	df	MS	F
Spousal Support	1593.25	2	796.62	.27
Social Support	405.34	2	202.67	3.76*
Negative Life Events	8.75	2	4.37	1.02
Economic Stress	181.96	2	90.98	.99
Work Stress	123.11	2	61.56	.49

* $p < .05$

Summary of Results

In accordance with the family stress model, it was expected that contextual socioeconomic stressors such as negative life events, economic stress, and work-related stress directly impact the emotional health and parenting effectiveness of parents. Also, it was expected that these negative effects would indirectly impact the mental health of their adolescent child through diminished parenting. Furthermore, it was expected that the negative effects of Time 1 contextual socioeconomic stressors on Time 2 parent variables and the subsequent effects of parent variables on Time 3 child outcome variables would be

moderated by levels of social and spousal support. The results of this study produced the following notable findings:

1. Economic stress had direct long-term consequences on the change in mental health of parents and their adolescent children, after controlling for Time 1 adolescent mental health.
2. The effect of economic stress on adolescent mental health was mediated through the mother's mental health and parenting practices.
3. The decline in the mother's mental health was associated with a corresponding decrease in her parenting practices. The more symptoms of depression, anxiety, and somatic symptoms the mother experienced, the less effective her parenting skills became.
4. The effect of economic stress on parenting practices was mediated through the mother's mental health.
5. Although ineffective parenting practices did not directly affect poor adolescent mental health, it indirectly affected the adolescent's mental health through the adolescent's perception of their mother's parenting practices. This suggested that how the child perceives their parent's parenting ultimately determines how they respond.
6. Social support exerted a highly significant direct effect on parental mental health and on parenting practices. Spousal support did not have a direct effect on parental mental health nor on parenting practices. Of the three negative contextual socioeconomic stressors, only economic stress exerted a moderate direct effect on parental mental health, but did not exert a significant direct effect on parenting practices.

7. Although spousal support did not have a direct effect on parent variables, spousal support significantly buffered the negative effects of economic stress on the single parent mother's parenting practices. The same buffering effects were not observed with high levels of social support.
8. Auto-regressive, cross-lagged, and contemporaneous models showed some evidence for causal effects, specifically between perception of ineffective parenting and adolescent mental health from Time 1 to Time 2.
9. Univariate latent growth curve analysis showed significant mean and variance in the growth factors for the mother's and adolescent's mental health, ineffective parenting practices, and adolescent's perception of parenting. Interlocking trajectory models showed that the level of mother's mental health did have moderate affect on the slope of parenting. The most significant effect was from the slope of mother's mental health to slope of ineffective parenting. The interlocking trajectories model showed a significant effect from level of adolescent's perception of parenting to level of adolescent mental health. Level of perception of parenting significantly predicted the level of adolescent mental health but not the slope of adolescent mental health. The slope of perception of parenting did not significantly predict slope of adolescent mental health.
10. Latent class growth analysis revealed three trajectory classes in adolescent mental health: Chronically low poor mental health group (Class 1), recovering group (Class 2), and escalating poor mental health group (Class 3). An analysis of variance with post-hoc comparisons showed that Class 1 and Class 2 differed significantly in their Time 1 mean levels of social support.

While social support had a direct effect on outcome variables, it did not significantly moderate the effects of contextual socioeconomic stressors. On the other hand, while spousal support did not have a direct effect on outcome variables, it did significantly moderate the effects of contextual socioeconomic stressors on outcome variables. It could be that social support tends to have direct benefits for the single parent mother (i.e., monetary and tangible aid), while spousal support has an indirect benefit for the single parent mother. These results suggest that the both social support and the supportive role of the ex-spouse is critical to the mother's mental well-being, effectiveness of parenting skills and ultimately to the mental health of the adolescent.

CHAPTER 6: DISCUSSION

Implications of Findings on Existing Literature

The broad goal of this study was to expand the research on the effects of contextual socioeconomic stressors and social support factors on family interactions and the mental health of individual family members. According to the family stress paradigm, negative stressors such as economic stress, work-related stress, and negative life events lead to poor mental health in parents, negatively impact the marital relationship, and undermine effective parenting. In turn, poor parental mental health, marital distress, and ineffective parenting are expected to have a cumulative negative impact on adolescent well-being. The purpose of this study was to explore the mechanisms through which contextual socioeconomic stressors may negatively impact parental and adolescent mental health and undermine effective parenting skills among single-parent mothers.

It was expected that the negative effects of these distal stressors on children are mediated through their parents. In addition, this study investigated the possible role of spousal support from the single-mothers' former spouse as moderator of these contextual stressors. Specifically, it set out to explore whether positive support from the former spouse significantly buffered the negative effects of economic stress, work-related stress, and negative life events on effective parenting and on the mental health of the single-parent mothers and their adolescent child. The implications of such findings would be that the benefits of positive spousal support may not be limited to married couples. Rather, divorced parents may also benefit from receiving support from their former spouses, particularly in the form of supportive parenting. Hence, the long-term outlook on the well-being and parenting

effectiveness of divorced single-parents does not necessarily have to be as bleak as many make it out to be.

This study expanded upon previous research in three broad ways:

1. By using a sample of divorced single-parent families, this study examined the influence of spousal support of the former spouse on parenting effectiveness among divorced mothers.
2. By using longitudinal panel data for divorced sample, the mediational and moderational processes as outlined in the family stress model was modeled so as to more clearly understand the temporal processes and mechanisms of influence.
3. By using new advanced methodological techniques for modeling longitudinal data, aspects of continuity and change in family relationships were examined in greater detail and with more precision.

The unique aspect of this study's moderating variable is that it is the level of spousal support among *divorced* parents, rather than married couples. Although previous studies have linked environmental stressors with mental health and parenting, very few have examined these constructs simultaneously, especially examining the moderating influences of the level of spousal support given by the parent's former spouse.

Consistent with Hypothesis 1, economic stress at Time 1 had a significant direct long-term effect on change in adolescent mental health at Time 3 after controlling for Time 1 adolescent mental health and before adding Time 2 parent variables (mother's mental health and ineffective parenting). Furthermore, as hypothesized, economic stress significantly predicted Time 2 parental mental health. The loss of significant direct effect on adolescent mental health after adding Time 2 parent variables suggests that the long-term effects of

economic stress is mediated through parental mental health and parenting practices. This was confirmed by the significant z-value as computed following Sobel's test of indirect effects.

The hypothesized direct effects of the other contextual socioeconomic factors, such as negative life events and work stress, were not observed. This may be due to the fact that there are gender differences in terms of the amount of distress caused by work and financial events. This explanation is consistent with a previous study demonstrating that husbands and wives respond differently to undesirable life events (Conger et al., 1993). Because the study sample only consisted of mothers, work-related stress may not significantly influence mother's mental health and parenting. However, women do tend to report more somatic complaints in response to financial stress. Since the mental health indicators were combined to form a latent factor in this study, it is not possible to tease apart the differential outcomes using the current models. However, future studies could certainly explore these differential outcomes in greater detail.

Another reason why significant effects of negative life events were not observed is that the measurement of life stress presents several significant difficulties (Pearlin, 1989). One of the issues is that researchers tend to only focus on the personal experience of negative life events without regard to structural context. The experience and the event cannot be separated. The charge is to consider the entire constellation of events and strains in the understanding and assessment of stress. In this regard, a possible limitation of this study is that it has not completely assessed all of the relevant domains of stress.

The positive coefficient suggests that the more economic stress the single mother experiences, the more likely she will develop symptoms of poor mental health (i.e., anxiety, depression, and somatic symptoms), which will in turn, negatively impact her parenting

skills. This finding is consistent with previous results showing that wives are more likely than husbands to report somatic complaints in response to financial stress (Conger et al., 1993). In the present study, the long-term end result is the increase in reports of symptoms of poor adolescent mental health: Increased anxiety, depression, and somatic symptoms.

Consistent with Hypothesis 2, poor parental mental health significantly predicted ineffective parenting practices. This finding is extremely important since it confirms previous studies that have concluded that a key mechanism required for an understanding of child adjustment involves parenting practices (Conger et al., 1995; Dishion et al., 1991). In other words, it is only when parenting practices are disrupted that the child is at risk for adjustment problems. The results of the present study suggest that the precursor to the disruption of parenting practices is the deterioration of parental mental health. This decline in mental health leads to subsequent corresponding decline in effective parenting practices. Such findings have implications for the development of parenting interventions and prevention programs. Subsequently, there has been an increase in experimental studies demonstrating promise for such programs that train parents to use more effective discipline to reduce adolescent antisocial behavior (Dishion et al., 1991), and holds promise for future research in the development of more effective parenting programs.

Consistent with Hypothesis 3, a test of direct effect of contextual socioeconomic stressors on Time 2 ineffective parenting practices showed that only economic stress exerted a direct, but only moderately significant, influence on parenting practices. This is not surprising considering the extensive body of literature demonstrating a strong link between economic stress and diminished parenting (Brooks-Gunn et al., 1997; Leinonen et al., 2002; Skinner, Elder, & Conger, 1992), which ultimately affects the long-term well-being of

children (Sobolewski et al., 2005). Consistent this body of literature, the results of this study demonstrated that the effect of economic stress on parenting is mediated through the single parent mothers' mental health.

The finding that ineffective parenting at Time 2 significantly predicted the child's perception of parenting at Time 3 is a significant one. The results of this study suggested that the effect of ineffective parenting on adolescent mental health is mediated through the adolescent's perception of their mother's parenting practices. This is consistent with previous studies demonstrating the important role of cognitions and attributions in family relationships (Fincham, 1998). Researchers have long recognized that perception is a critical component in the understanding of family processes and intra-familial relationships (Lavee et al., 1985) and that the impact of a stressful event on a child is best understood by considering the child's interpretation of the event (Compas, 1987; Kagan, 1983). In support of this perspective, Emery and O'Leary (1982), for example, found that boys' perceptions of marital conflict were a stronger predictor of their adjustment than either marital satisfaction or maternal ratings of inter-parental conflict and marital satisfaction were not as consistently related to child adjustment as child reports of marital conflict. Only child reports of inter-parental conflict correlated with child adjustment assessed across different informants. The implication of such findings is that future studies should not only include parents' self-reports; future studies examining parent-child relationships should include observer reports and child reports as much as possible.

A key finding of the present study was that there was a significant difference in the influence of economic stress on parenting depending on the level of support of former spouse experienced by the single parent mother. In other words, the single-parent mother's

relationship quality with her former spousal buffered the negative effects of economic stress on her parenting practices at Time 2. Studies have found supportive spousal relationships to be moderators of stressors. For example, Noor (2002) found that spousal support moderated the relationship between work variables (i.e., long work hours, autonomy, tedium and overload) and conflict. This is consistent with an earlier study examining the moderating effect of spousal support on the negative impact of parental overload on family-work conflict (Aryee et al., 1999). The implication of these findings for single-parent mothers is that although they are at-risk for being adversely affected by environmental stressors due to both a loss of a significant support structure and the negative events associated with the divorce process itself, the negative effects accompanying divorce do not necessarily have an unavoidable and irreversible influence on the mother and her children. In fact, the present study demonstrated that the relationship with the former spouse is a modifiable risk and also a potential protective factor that may buffer the negative effects of stressors in the lives of single-parent mothers. The finding of this study is consistent with a previous study demonstrating that the level of spousal support was positively related to supportive parenting; that is, spousal support moderated the impact of economic strain on supportive parenting; however, it was only true for mothers and not fathers (Simons, Lorenz, Conger, & Wu, 1992).

One surprising finding was that social support exerted a highly significant direct effect on parental mental health and on parenting practices, but not a buffering effect. This may be due in part to the fact that the measure of social support included tangible support, which included mostly support in the form of food, shelter, money, or transportation. These forms of support have an immediate, but short-lived benefit, while a relationship with the

former spouse is ongoing and changes in the patterns of parenting are also ongoing and developing over time. Therefore, social support may have exerted a direct significant effect on the mother's well-being, while relationship with former spouse had a buffering effect. Although gender differences in the effects of partner support are not hypothesized in this study, studies have noted how women and men may differ in their social networks. Specifically, it has been suggested that women tend to rely more on contextual relationships (i.e., extended family and friends) and therefore have a larger social network that is more intimate and offers support in multiple forms and from multiple sources. Men, on the other hand, often rely solely on their spouses as the support provider (Glynn et al., 1999; Greenglass, 1982; Hobfoll, 1986, 1998; Klauer & Winkeler, 2002; Knoll & Schwarzer, 2002; Schwarzer, 2003).

The use of latent class growth analysis (LCGA) and general mixture modeling (GMM) approaches has recently grown in popularity in family research, but still remains an understudied area of research. The contribution of the present study is that LCGA results showed that there is indeed heterogeneity in growth patterns of adolescent mental health. Latent class growth analysis revealed three trajectory classes in adolescent mental health: Chronically low poor mental health group (Class 1), recovering group (Class 2), and escalating poor mental health group (Class 3). An ANOVA with post-hoc comparisons showed that Class 1 and Class 2 differed significantly in their Time 1 mean levels of social support. This finding is consistent with previous studies demonstrating heterogeneity of adolescent mental health growth patterns. For example, Rodriguez, Moss, and Audrain-McGovern (2005) demonstrated that there were three classes of growth trajectories for adolescent depressive symptoms (high, medium, and low). Stoolmiller, Kim, and Capaldi

(2005) identified four latent trajectory classes for depressive symptoms: the very low, the moderate-decreasing, the high-decreasing, and the high-persistent classes.

It is important to note that the profiles of the growth patterns will differ from study to study, depending on how mental health was measured. In the present study, mental health was a combination of depression, anxiety, and somatic symptoms. Because it is a composite measure, it will look differently than growth patterns based solely on measures of depression. The differing numbers of classes across different studies is not a cause for concern, however, since the number of classes identified depends on the inclusion of additional model covariates, study sample (age range), and the measurements used. The methodological implication of this finding is that traditional growth analysis approaches (e.g., univariate latent growth analysis) assume population homogeneity and assign a single estimate for each growth parameters for the entire population. Yet, theory and previous research often point to population heterogeneity. That is, single estimates of growth parameters may not be accurate, and requires identifying distinct sub-populations.

Theoretical Implications

The results of this study are consistent with previous research showing that economic hardship has an adverse influence on the psychological well-being of individual family members and on the quality of intra-familial relationships (Conger, McCarthy, Young, Lahey, & Kropp, 1984; Conger et al., 1990, 1991, 1992, 1993; Elder, 1974; Elder, Conger, Foster, & Ardelt, 1992; Liker & Elder, 1983; Whitbeck, Simons, Conger, Lorenz, Huck, & Elder, 1991; Lempers, Clark-Lempers, & Simons, 1989). Specifically, the results of the structural equation models showed that economic stress at Time 1 had both a long-term direct and an indirect affect on adolescent mental health at Time 3, even after controlling for Time

1 adolescent mental health. This finding is significant because it shows that economic stress at family of origin has far-reaching persistent affects on adolescent outcome, particularly mental health (cf. Wickrama et al., 2005).

Furthermore, this study demonstrated that the process that accounts for the transmission of socioeconomic adversity from the context to the individual is the intergenerational transmission of socioeconomic adversity from parent to children, from one generation to the next. This mechanism is consistent with the causation hypothesis model, which assumes that there are social determinants of individual-level mental health. In this study, a social determinant, economic stress, is observed to have a long-term causal effect on adolescent mental health. This is consistent with previous studies using latent growth curve models to link divorce to individual-level psychological distress (Lorenz et al., 1997, 2006). Yet the results do not necessarily preclude support for the interactionist perspective (Conger & Donnellan, 2007), where an individual characteristic such as mental illness causes a downward "spiral of perniciousness," which eventually leads to further and further behavioral, mental, and most importantly, social problems (Miech et al., 1999). In this way, health problems may be transmitted across generations, and mental illness may be transmitted to offspring.

Another interesting finding of this study is that the long-term effect of economic stress on adolescent mental health was moderated by the level of spousal support received by the divorced mother from her former spouse. The level of support from former spouse as a buffer of the negative effects of contextual socioeconomic stress is an area of family research that has not been extensively studied. Yet, previous studies have demonstrated that divorce is concomitant with a myriad of negative contextual socioeconomic stressors and individual

outcome, including negative life events, economic hardship and financial strain, work-related problems, decreased family functioning, and poor physical and mental health (Lorenz, Wickrama, Conger, & Elder, 2006; Wallerstein, 1991). As a result, negative contextual socioeconomic stressors coupled with troubled family relationships can have a cascading effect on the physical and mental health of adolescent children as well. Many studies have demonstrated that a supportive and warm marital relationship between parents leads to positive parenting practices, which, in turn, may lead to various positive child outcomes, including improved adolescent mental health (Simons, Lorenz, Conger, & Wu, 1992).

The results of the test of moderation showed that the effect of economic stress on ineffective parenting was moderated by the level of support from former spouse. When the level of spousal support was low, economic stress had a significant impact on parenting practices, but when the level of spousal support was high, there was no significant direct effect of economic stress on parenting.

Finally, an examination of the linkages and the mediating variables connecting contextual socioeconomic stressors to individual-level adolescent mental health outcome showed several mechanisms at work. After demonstrating the long-term direct effect of economic stress on adolescent mental health, parent variables such as mental health of mother and ineffective parenting practices were added to the model. As expected, economic stress no longer exerted a significant direct effect on ineffective parenting, after including parental mental health and ineffective parenting practices in the model. This suggests that the effect of economic stress on parenting is mediated through the single parent mothers' mental health and her ineffective parenting practices. To test the significance of the indirect effect, the recommendations from MacKinnon, Warsi, and Dwyer (1995) were followed. The

significant of the indirect paths were assessed using the modified Sobel test of indirect effect, which suggested a significant indirect effect of economic stress on ineffective parenting practices. Economic stress has a longer-enduring and an overall greater net effect on adolescent mental health than negative life events and work stress. This is consistent with previous studies that have established a strong link between SES and mental illness (Miech et al., 1999).

As mentioned previously, another unique aspect of this study is the inclusion of the adolescent's perception of parenting in the model. To test for direct effects of parenting practices at Time 2 on adolescent mental health and Time 3, adolescent mental health latent variable was regressed on parenting practices latent variable, controlling for Time 1 adolescent mental health (Figure 20). The results of this study suggest that a positive change in ineffective parenting leads to a corresponding positive change in the adolescent's perception of their parent's parenting practices. Furthermore, the results show that the child's perception of parenting significantly predicts the child's mental health. These results collectively suggest that although child's perception may not mediate the effects of parenting practices on adolescent mental health in the traditional Baron and Kenny (1991) sense, ineffective parenting practices may still exert an indirect effect on adolescent mental health. The theoretical implication of this finding is that perception of parenting plays an extremely important role in the determination of adolescent mental health. In future studies examining the effects of parenting practices, employing a multi-method approach using a combination of mother's self-reports, observer reports, and adolescents' reports will increase the reliability and validity of the measure. The methodological implication of this finding is that while mediation did not occur according to the traditional Baron and Kenny (1991) sense, the

results supported the idea of linkage, whereby the long-term effects of economic stress on adolescent mental health was sustained by several intermediary variables, including mother's mental health, ineffective parenting practices, and adolescents' perception of parenting.

Limitations of Study

While the present study provided many valuable insights, it is important to recognize its limitations. First and foremost, the generalizability of findings must be questioned for several reasons. Since the family stress paradigm was tested and refined most extensively with married couples, the question remains to what extent it can be applied to families with only single-parent mothers. The authors of a previous study using the family stress paradigm suggested that the postulated model is operative only for two-parent families and that the life experiences of single parents are unique (Conger et al., 1995). It may be the case that single parents experience higher levels of stress, and therefore any new acute stressor event is more likely to directly affect parenting behavior or child adjustment in an already stressed family. Perhaps future research may refine or even redefine the family stress paradigm for different families, such as families headed by divorced single mothers.

Also, while the sample is representative of many rural populations in the U.S., the subjects were all from a single rural Midwestern state. Also again, the present study consisted of only Caucasian single-parent mothers and Caucasian adolescents. Therefore, the study suffers from the lack of a complete nationwide random selection, and the ability to generalize the findings may be compromised. Furthermore, previous studies have noted that there are gender differences in the effects of socioeconomic contextual stressors on parents and in subsequent parent-child relationships (Conger et al., 1993; Conger, Patterson, & Ge, 1995).

Second, most of the data used in this study were gathered from self-report questionnaires. A mono-method approach to data collection may lead to biased results. The inclusion of the observer ratings for the mother's parenting practices was one effort to mitigate this problem. Past studies have often shown that parents' ratings of their behaviors often differ significantly from their children's ratings of their behavior. To address this issue, adolescent's perception of parenting was also included in this model rather than just observer report or relying on parents' self-report.

Third, because this is a longitudinal study, attrition remains a threat to drawing inferences to larger population. Also, with the threat of attrition comes a shrinking sample size, rendering complicated SEM analyses prohibited. Related to the sample size issue is the limitation of recent analyses, such as latent class growth analysis. Because these models are so complicated and large, they require both a larger sample size as well as increased computational power to estimate more complicated models.

Fourth, with regard to latent class and general mixture analysis, there are no agreed upon approaches for determining the number of classes in the analyses. Tests of model fit such as the Lo-Mendell-Rubin test, BIC vs. adjusted BIC, etc., are currently being tested. At the moment, no clear consensus exists at the moment regarding cutoff criteria for choosing a latent class model.

Practical Implications

More often than not, children end up in the custody of the mother after divorce. It is estimated that more than 85 percent of children whose parents are divorced are in the custody of their mothers (Furstenberg & Cherlin, 1991). Considering the high prevalence of post-divorce children living with their mothers, the results of the present study underscores the

need for special attention to be given to the unique experiences of post-divorce, single-parent motherhood. As noted at the beginning of this paper, single-parent mothers experience a unique set of challenges. Often, single-parent motherhood is concomitant with poverty, poor parenting, and several other health-related risk factors. However, a divorce or separation does not necessarily preclude the chance for post-divorce children from experiencing positive, warmth, and effective parenting from their divorced parents. Theoretical models have been proposed to account for the phenomenon of post-divorce parenting (e.g., Abidin, 1992; Abidin & Brunner, 1995). In such research, many different terms have been used to describe post-divorce parenting arrangements. Terms such as *coparenting, shared parenting, parenting alliance* and *parenting partnerships* refer to the involvement of both parents in childrearing after divorce and encompass a range of cooperative efforts between parents. Shared or joint custody refers to legal arrangements and may or may not be used synonymously with the above terms. Shared parenting does not necessarily involve a fully equal division of childrearing responsibility and caretaking, and mothers continue to be the primary resident parent even when joint legal custody is designated (Seltzer & Bianchi, 1988). Thus, the difference between "coparenting" and couple or marital relationship is the concept of a shared parenting role. That is, regardless of marital status or cohabitation, individuals may work together in their roles as parents. In fact, research indicates that the coparenting relationship is more powerfully and proximally related to parenting than other aspects of the couple relationship. When the general couple relationship and coparenting are compared in the same study, coparenting often is found to be of greater significance. For example, for married couples, Abidin and Brunner (1995) found that the *parenting alliance, not marital adjustment,* is significantly associated with parenting style. Bearss and Eyberg

(1998) reported that the parenting alliance had a stronger relationship with child problems than did marital adjustment. More recently, Feinberg, Neiderhiser, Reiss, Hetherington, and Simmens (2000) confirmed the findings of these studies in their analysis of data from nondivorced couple sample. Similar findings have been obtained for divorced parents as well (see Whiteside & Becker, 2000 for review; see also Camara & Resnick, 1989; Ihinger-Tallman, Pasley, & Beuhler, 1995; Feinberg, 2002).

Finally, this study demonstrated that poor parental mental health is a significant determinant of ineffective parenting practices. This finding is extremely important since it confirms previous studies that have concluded that a key mechanism required for an understanding of child adjustment involves parenting practices (Conger et al., 1995; Dishion et al., 1991). Such findings have implications for the development of parenting interventions and prevention programs. Subsequently, there has been an increase in experimental studies demonstrating promise for such programs that train parents to use more effective discipline to reduce adolescent antisocial behavior (Dishion et al., 1991), and holds promise for future research in the development of more effective parenting programs.

APPENDIX 1. SAS PROC LCA Syntax

A. Example of SAS Procedure for Latent Class Analysis (LCA)

```
PROC LCA DATA=DRUG OUTPOST=DRUG_PP OUTEST=DRUG_EST;
   TITLE1 'Three-class model with two groups and a covariate';
   TITLE2 'Measurement invariance across groups';
   TITLE3 'Posterior probabilities saved to SAS data file';
   NCLASS 3;
   ITEMS x1 x2 x3 x4 x5 x6;
   CATEGORIES 2 2 2 2 2 2;
   GROUPS sex;
   GROUPNAMES male female;
   MEASUREMENT GROUPS;
   COVARIATES age;
   REFERENCE 1;
   SEED 409621;
RUN;
```

APPENDIX 2. Mplus Syntaxes

A. Mplus syntax example for modeling univariate latent growth curve for adolescent mental health

```
Title:
    UNIVARIATE GROWTH CURVE (ADOL MENTAL HEALTH)
Data:
        file is 'I:\adolMH 123 onlyDAT.dat';
Variable:
        names are AMH1 AMH2 AMH3 ;
        usevar = AMH1-AMH3;
        MISSING = ALL (999);
Analysis:
        TYPE = MISSING H1;
Model:
        i s | AMH1@0 AMH2@1 AMH3@2 ;
Output:
        sampstat standardized tech1 ;
```

B. Mplus syntax example for modeling univariate latent growth curve for adolescent perception of ineffective parenting

```
Title:
        UNIVARIATE GROWTH CURVE (ADOL PERCEPTION)
Data:
        file is 'I:\percep 123 onlyDAT.dat';
Variable:
        names are percep1 percep2 percep3 ;
        usevar = percep1-percep3;
        MISSING = ALL (999);
Analysis:
        TYPE = MISSING H1;
Model:
        i s | percep1@0 percep2@1 percep3@2 ;
Output:
        sampstat standardized tech1;
```

C. Mplus syntax example for modeling interlocking trajectories for adolescent perception of ineffective parenting and adolescent mental health

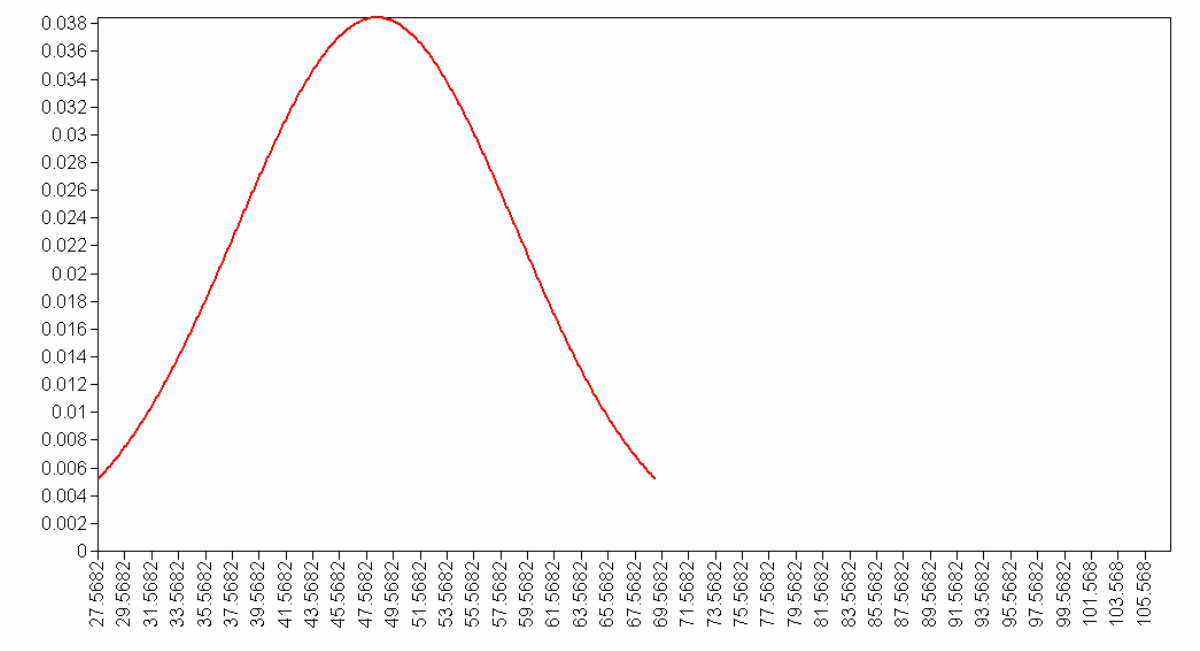
```
Title:
        INTERLOCKING TRAJECTORIES (PERCEPTION OF PARENTING
        & ADOL MENTAL HEALTH)
Data:
        file is 'I:\percep123 & AMH123 only.dat';
Variable:
        names are percep1 percep2 percep3 AMH1 AMH2 AMH3 ;
        usevar = percep1-AMH3;
        MISSING = ALL (999);
Analysis:
        TYPE = MISSING H1;
Model:
        iPP sPP | percep1@0 percep2@1 percep3@2 ;
        iAMH sAMH | AMH1@0 AMH2@1 AMH3@2 ;
        iAMH ON iPP ;
        sAMH ON iPP sPP ;
Output:
        sampstat standardized tech1;
```

D. Mplus syntax example for latent class growth analysis on adolescent mental health

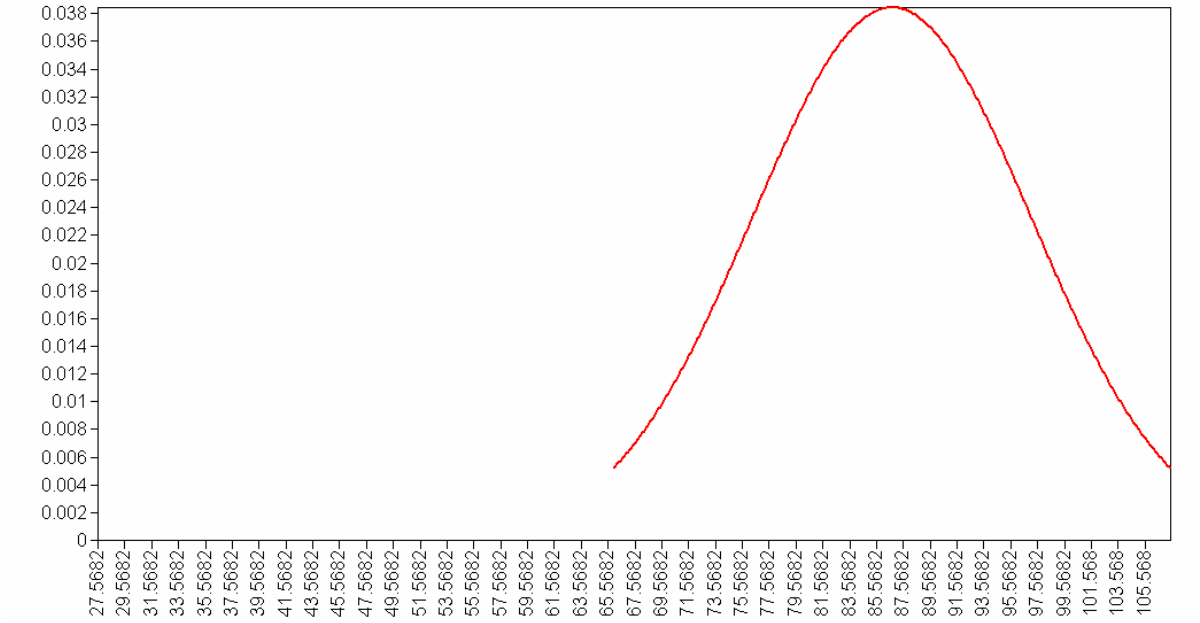
```
  TITLE:  LATENT CLASS GROWTH ANALYSIS
            ADOLESCENT MENTAL HEALTH (WAVES 1-3)

  DATA:   FILE IS
          'U:\adolpercep & adolMH.DAT';

  VARIABLE:   NAMES ARE
               famid
               AMH1 AMH2 AMH3
              ;
               USEVARIABLES ARE
                AMH1 AMH2 AMH3
              ;
               IDVARIABLE = famid ;
               MISSING = ALL (999) ;
               CLASSES = c(3) ;

SAVEDATA:   FILE IS U:\3CLASSpostprobs;
            RECORDLENGTH = 211;
            save = cprobabilities ;

ANALYSIS:   TYPE = mixture missing ;
              STARTS = 100 10 ;

MODEL:      %OVERALL%
                I S | AMH1@0 AMH2@1 AMH3@2 ;
OUTPUT:     sampstat TECH1 tech4 tech8 ;
PLOT:       SERIES = AMH1-AMH3 (s);
            TYPE = PLOT3 ;
```

APPENDIX 3. Mplus Latent Class Growth Analysis Output

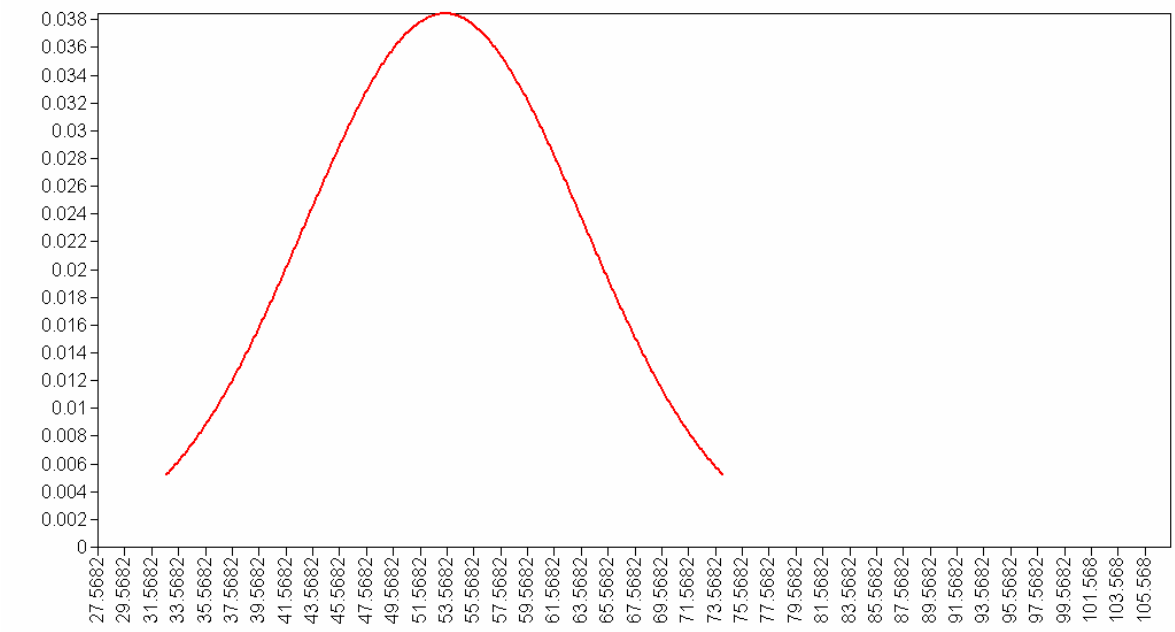
A. Estimated mixture distribution for AMH, Class 1



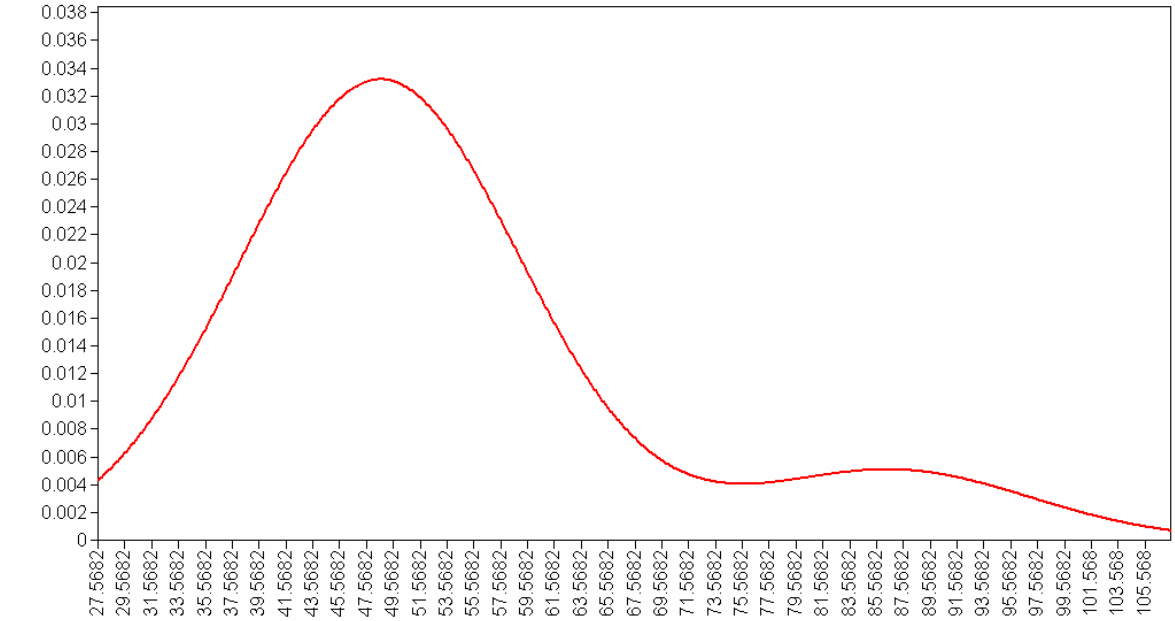
B. Estimated mixture distribution for AMH, Class 2



C. Estimated mixture distribution for AMH, Class 3



D. Estimated mixture distribution for AMH, Overall Combined



APPENDIX 4. PROC LCA and Mplus LCA Background

Lanza and colleagues (2006) describe the mathematical model of SAS PROC LCA as follows. Three sets of parameters are provided in the PROC LCA output:

(1) Gamma (γ): latent class membership probability

(2) Beta (β): logistic regression coefficient for covariates, predicting class membership

(3) Rho (ρ): item-response probability

All of these three parameters can be conditioned on group.

The likelihood equation modeling contribution of individual i is as follows:

$$P(Y_i = y_i) = \sum_{l=1}^{C} \gamma_1(x_i) \prod_{m=1}^{M} \prod_{k=1}^{r_m} \rho_{mk/l}^{I(y_{im}=k)}$$

where C denotes the latent classes and assume they are derived from a set of m binary items. We will assume the outcome variable is continuous and is denoted by x. Let $Y_i = (Y_{i1}, \ldots, Y_{iM})$ represent individual i's response to the M items where $Y_{iM} = 1, 2, \ldots, r_m$. Let $L_i = 1, 2, \ldots, C$ be the latent class membership of individual i and let $l(y = k)$ be the indicator function which equals 1 if response y equals k and 0 otherwise. Also, x_i represents the value of the covariate for individual i and that its value can relate to the probability of membership in each latent class, γ.

β parameters are estimated in logistic regressions for the γ parameters, allowing the γ parameters to be expressed as:

$$\gamma_l(x_i) = P(L_i = l \mid x_i) = \frac{\exp\{\beta_{0l} + x_i\beta_{1l}\}}{1 + \sum_{j=1}^{C-1} \exp\{\beta_{0l} + x_i\beta_{1l}\}}$$

for $l = 1, \ldots, C\text{-}1$ with class C as the reference group. This allows us to estimate the log-odds that an individual falls in latent class l relative to reference class C. For example, if Class 2 is the reference group, the log-odds of membership in Class 1 relative to Class 2 for an individual with value x_i on the covariate is:

$$\log\left(\frac{\gamma_1(x_i)}{\gamma_2(x_i)}\right) = \beta_{01} + \beta_{11}x_i$$

Exponentiated beta parameters are odds ratios, reflecting the increase in odds of class membership (relative to reference class C) corresponding to a one-unit increase in the covariate. Multiple covariates can be included simultaneously.

PROC LCA handles missing data on the latent class indicators and data are assumed to be missing at random (MAR). A test of the null hypothesis that data are missing completely at random (MCAR) appears in the output. See Appendix 1 for an example of SAS PROC LCA syntax.

Using structural equation modeling in Mplus software, LCA with discrete or polytomous latent class indicators can be modeled as follows:

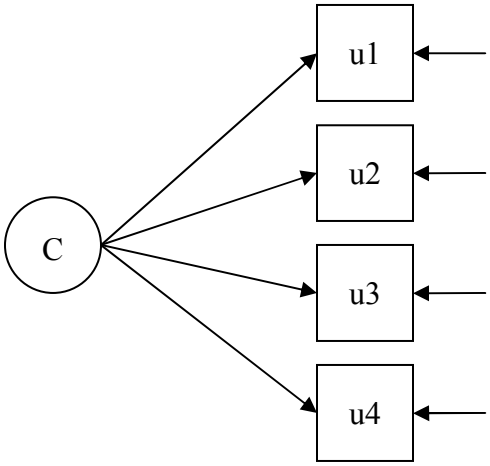


Figure 51. Latent class analysis with discrete or polytomous indicators.

where discrete or ordered polytomous latent class indicators are denoted by *u1-u4* and *c* represents the categorical latent variable. The arrows from *c* to the latent class indicators indicate that the thresholds of the latent class indicators vary across the classes of *c*. This implies that the probabilities of the latent class indicators vary across the classes of *c*. The arrows correspond to the regressions of the latent class indicators on a set of dummy variables representing the categories of *c*. See appendix for example Mplus syntax for modeling LCA with polytomous latent class indicators using automatic starting values with random starts.

APPENDIX 5. Sample Size Determination

A. Minimum Sample Size to Achieve Power of 0.80 for Selected Levels of Degrees of Freedom (*df*) (MacCallum, Browne, & Sugawara, 1996).

Df	**Minimum *N* for test of close fit**	**Minimum *N* for test of not-close fit**
2	3,488	2,382
4	1,807	1,426
6	1,238	1,069
8	954	875
10	782	750
12	666	663
14	585	598
16	522	547
18	472	508
20	435	474
25	363	411
30	314	366
35	279	333
40	252	307
45	231	286
50	214	268
55	200	253
60	187	240
65	177	229
70	168	219
75	161	210
80	154	202
85	147	195
90	142	189
95	136	183
100	132	178

B. List of Critical Noncentrality Parameters ($\delta_{1-\beta}$) by Degrees of Freedom and Power = .80 and .90 at α = .05. (from Kim, 2005).

Df	***Power = .80***	***Power = .90***	***Df***	***Power = .80***	***Power = .90***
1	7.849	10.507	26	23.200	28.784
2	9.635	12.654	27	23.546	29.194
3	10.903	14.171	28	23.885	29.596
4	11.935	15.405	29	24.219	29.991
5	12.828	16.469	30	24.547	30.379
6	13.624	17.419	35	26.107	32.225
7	14.351	18.284	40	27.557	33.940
8	15.022	19.083	45	28.918	35.549
9	15.650	19.829	50	30.204	37.069
10	16.241	20.532	60	32.593	39.891
11	16.802	21.198	70	34.787	42.483
12	17.336	21.833	80	36.829	44.893
13	17.847	22.439	90	38.745	47.155
14	18.338	23.022	100	40.556	49.293
15	18.811	23.583	125	44.721	54.206
16	19.268	24.125	150	48.483	58.643
17	19.710	24.650	175	51.942	62.721
18	20.139	25.158	200	55.160	66.515
19	20.555	25.652	225	58.182	70.077
20	20.961	26.132	250	61.039	73.444
21	21.356	26.600	300	66.353	79.706
22	21.741	27.057	350	71.238	85.462
23	22.118	27.503	400	75.785	90.818
24	22.486	27.939	450	80.055	95.848
25	22.847	28.366	500	84.093	100.604

C. Step-By-Step Instruction for Computing Proposed Sample Size for Each Fit Index (from Kim, 2005).

The first three steps for computing a proposed sample size for each fit index are the same for all four fit indexes (CFI, RMSEA, Steiger's γ, Mc):

1. Identify a SEM model.
2. Compute the degrees of freedom (*df*) for the model.
3. Compute the noncentrality parameter, $\delta_{1-\beta}$.

CFI

1. Choose a value of CFI (e.g., CFI = .95).
2. Compute F_B using the following equation:

$$F_B = \log|I| - \log|\rho| + tr(\rho I) - p = -\log|\rho|$$

where ρ is the correlation matrix based on the values of the model parameters and *I* is the identity matrix of *p x p*.

3. Compute $\delta_{1-\beta}$. (or see Appendix 3B)
4. Compute a proposed sample size using the following equation:

$$N_{CFI} = \frac{\delta_{1-\beta} + df_B(1-CFI)}{F_B(1-CFI)} + 1$$

RMSEA

1. Choose a value of ε (e.g., ε = .05).
2. Compute a proposed sample using the following equation:

$$N_{\varepsilon} = \frac{\delta_{1-\beta}}{\varepsilon^2 df} + 1$$

Steiger's γ

1. Choose a value of γ (e.g., γ = .95).
2. Compute a proposed sample size using the following equation:

$$N_{\gamma} = \frac{2\gamma\delta_{1-\beta}}{p(1-\gamma)} + 1$$

Mc

1. Choose value of Mc (e.g., Mc = .95)
2. Compute a proposed sample size using the following equation:

$$N_{Mc} = -\frac{1}{2}\left(\frac{\delta_{1-\beta}}{\log(Mc)}\right) + 1$$

APPENDIX 6. Table of Chi-Square Differences in Test for Moderation by Spousal Support and Social Support

A. Change in Path Coefficients Across Level of Spousal Support (High vs. Low)

Path			Chi-square Change	Change in df
T1 Economic Stress	→	T2 Ineffective Parenting	5.137*	1
T1 Work Stress	→	T2 Ineffective Parenting	2.774	1
T2 Parental Mental Health	→	T2 Ineffective Parenting	0.591	1
T1 Negative Life Events	→	T2 Ineffective Parenting	0.027	1
T1 Negative Life Events	→	T2 Parental Mental Health	0.784	1
T2 Ineffective Parenting	→	T3 Adolescent Mental Health	0.206	1
T1 Work Stress	→	T2 Parental Mental Health	0.891	1
T1 Economic Stress	→	T2 Parental Mental Health	0.621	1
T2 Ineffective Parenting	→	T3 Adolescent's Perception	0.084	1
T3 Adolescent Perception	→	T3 Adolescent Mental Health	1.032	1

$^{+}p < .10$ * $p < .05$ ** $p < .01$ *** $p < .001$

B. Change in Path Coefficient Across Level of Social Support (High vs. Low)

Path			Chi-square Change	Change in df
T1 Economic Stress	→	T2 Ineffective Parenting	0.657	1
T1 Work Stress	→	T2 Ineffective Parenting	0.039	1
T2 Parental Mental Health	→	T2 Ineffective Parenting	0.071	1
T1 Negative Life Events	→	T2 Ineffective Parenting	0.255	1
T1 Negative Life Events	→	T2 Parental Mental Health	0.056	1
T2 Ineffective Parenting	→	T3 Adolescent Mental Health	0.4	1
T1 Work Stress	→	T2 Parental Mental Health	2.506	1
T1 Economic Stress	→	T2 Parental Mental Health	1.26	1
T2 Ineffective Parenting	→	T3 Adolescent's Perception	0.929	1
T3 Adolescent Perception	→	T3 Adolescent Mental Health	0.06	1

$^{+}p < .10$ * $p < .05$ ** $p < .01$ *** $p < .001$

APPENDIX 7. Approaches to Addressing Problem of Missing Data

Missing data presents a technical problem since most multivariate methods require complete data. Traditionally, incomplete data are often dealt with by listwise (LD) or pairwise (PD) deletion methods, which omit entire records, or pairs of variables, with missing values. Of these, listwise or case deletion is the most common method used to deal with missing data. Sometimes a researcher will substitute sample means for the missing values. All three approaches aim to fix up the data so that they can be analyzed by methods designed for complete data but are ad hoc and have little theoretical justification. The methods of full-information maximum likelihood (FIML) and multiple imputation (MI), in contrast, have long been known as a theory-based approach to the treatment of missing data. These two methods are rooted in statistical theory and are preferred over the traditional approaches (Collins, 2006). When the assumptions underlying these procedures are met, they restore much statistical power and eliminate bias due to missing data; even when the underlying assumptions are not met, modern missing data procedures are an improvement over ad hoc methods (Collins, 2006; Collins et al., 2001).

The FIML method works by using all of the available information in the observed data, including mean and variance for the missing portions of a variable, given the observed portions(s) of other variables (Wothke, 1998). FIML assumes multivariate normality and maximizes the likelihood of the model with the observed data. FIML also assumed MAR. Recent research into the sensitivity of FIML to violations of these two requirements showed some robustness of the method to mild deviations from these assumptions (e.g., Collins, et al., 2001; Schafer & Graham, 2002). Currently, structural equation modeling software such

as AMOS (Arbuckle, 2003), LISREL (du Toit & du Toi, 2001), Mx (Neale, 1997), and Mplus (Muthén & Muthén, 2004) have incorporated FIML into the programs.

The most commonly practiced methods for structural equation modeling (SEM) with missing data apply complete-data ML estimation to covariance matrices that have been somehow corrected. Such corrections can be:

(a) *listwise deletion* (LD), which excludes from the calculations all records with missing values on any of the variables,

(b) *pairwise deletion* (PD), by which each sample covariance between two variables is computed from pairwise-complete data, excluding cases with missing values on one or both of the variables, or

(c) *mean-imputation*, which replaces the missing values of a variable by the mean of its observed values.

Several studies have compared the performance of these different missing data methods using simulation. For example, Brown (1983) compared LD, PD, mean imputation and FIML methods using Monte-Carlo simulation in the factor analysis context. Brown (1994) studied the performance of LD, PD and mean imputation by Monte-Carlo simulation in the context of structural equation modeling. Little and Rubin (1987) reviewed all four methods in the general multivariate case. All three studies were critical of mean-imputation, LD and PD methods, citing biased and/or inefficient estimates as well as the increased potential of obtaining indefinite sample covariance matrices. Brown (1983) qualifies his comments about LD, PD, and mean imputation with respect to frequency and type of the missing data. Until recently, model-based imputation of missing values was rarely used in structural equation modeling, even though it is well known in the statistical literature (Kim &

Curry, 1977; Roth, 1994). In particular, the EM algorithm (Dempster, Laird & Rubin, 1977), which implements the FIML approach by repeated imputation estimation cycles, has recently been used as a method for estimating means and covariance matrices from incomplete data (Graham, Hofer, Donaldson, et al., 1997; Graham & Hofer, 2000; Rovine, 1994).

FIML assumes multivariate normality, and maximizes the likelihood of the model given the observed data. The theoretical advantages of this full information method are widely recognized, and it is now implemented in the Amos and Mx structural equation modeling programs. Unfortunately, theory has not had much influence on practice in the treatment of missing data. In part, the under-utilization of maximum likelihood estimation in the presence of missing data may be due to the unavailability of the method as a standard option in packaged data- analysis programs. There may also exist a (mistaken) belief that the benefits of using maximum likelihood (ML) estimation rather than conventional missing-data techniques will in practice be small.

Multiple imputation (MI) as a method for dealing with incomplete data was first proposed by Rubin in 1978 and developed further by Little and Rubin (1987). MI expands on the single imputation method, whereby each missing value is replaced by simulated values, thereby generating a predetermined number (*m*) of versions of complete data sets. The advantage, then, of MI over single imputation (i.e., EM) is that while single imputation underestimates the variability among the missing values, MI aims to preserve the entire distribution of the dataset, rather than merely giving a point estimate. The advantage of MI over maximum likelihood (ML) is that it is computationally much simpler for most practical solutions. However, as it will be addressed later, MI is not the magic cure-all and does not necessarily have an edge over FIML.

MI does not impute for the sake of replacing the missing value itself, rather it imputes the values with the goal of preserving the overall data distribution, i.e., both mean estimates, variances, and standard errors. The newly "created" *m* datasets are then analyzed just like a normal complete dataset would be. Because each dataset is analyzed individually, each analysis produces a unique set of estimates. After analyzing all *m* datasets, the results are combined using a rule created by Rubin (1987), sometimes simply referred to as, "Rubin's Rule." Using this rule, the *m* sets of results are combined to obtain a final, overall estimate and appropriate standard errors, which take into account the uncertainty due to the missing data values. For most applications, three to give imputations have been suggested as adequate for obtaining estimates. Rubin (1987) showed that the efficiency of an estimate based on *m* imputations is approximately

$$(1+\gamma/m)^{-1}$$

where γ is the fraction of missing information for the quantity being estimated. For 40% missing information, $m = 5$ imputations give 93% efficiency whereas $m = 10$ imputations increase efficiency only to 96%.

Of the available methods, FIML and multiple imputation (MI) are advantageous over the traditional approaches and seem to be the best methods especially with large samples (Acock, 2005). Until recently, it has been argued that MI is better since it is more generally applicable and MI makes it easier to include auxiliary variables (Collins, Schafer, & Kam, 2001). However, recent advances in methodological approaches have enabled models to allow auxiliary variables with FIML (Graham, 2003). As practiced, FIML may be better than MI because FIML estimates may have more power. In the long run, however, FIML and MI

are equivalent, especially when the number of imputations is set high enough in MI (Collins, Schafer, & Kam, 2001; Graham, 2003).

In the end, what seems to matter is the set of variables used in either the MI or FIML procedure. With FIML, this set of variables is typically confined to those included in the particular scientific analysis at hand, even if this means omitting one or more variables that contain information necessary to the missing data model. For example, in an analysis examining the relation between parental characteristics and offspring self-reported substance use, offspring reading test scores may not be included because this variable is not of immediate scientific interest. However, if slow readers are less likely to complete the questionnaire, then omitting this variable may mean that missing data will affect the results even though a ML procedure was used.

Because with MI the imputation is typically done separately from scientific data analyses, many additional variables in a data set easily can be included in the imputation process. Thus the likelihood of omitting a variable important to the missing data model is greatly reduced. This seems to be an advantage of MI over FIML currently, but it is not an inherent advantage, because additional variables can be included in ML for the purpose of enhancing the missing data model (Graham, 2003). Unfortunately, most ML software makes this more difficult than it needs to be, and many users are not aware that adding such variables is either beneficial or possible. The good news is that software is available for performing multiple imputation (MI). NORM (Schafer, 1999) is a stand-alone application for PCs that performs MI under a multivariate normal model. The multiple imputation procedure (PROC MI) in SAS Version 8.02 also creates multiply-imputed datasets for incomplete

multivariate data. One the *m* complete datasets are analyzed using a standard SAS procedure, PROC MIANALYZE procedure can be used to combine the results, using Rubin's rule.

APPENDIX 8. Power Analysis in SEM

Any researcher who wishes to design a study and collect data for the study must face the mystery that often those who choose to endeavor: "What sample size do I need for my study?" Although there is universal agreement that the larger the sample, the more stable the parameter estimates, there is no agreement as to what constitutes "large". Attempts have been made simple rules-of-thumb in SEM. One of the more popular suggestions is that the sample size should always be more than 10 times the number of free model parameters (cf. Bentler, 1995; Hu et al., 1992). Such that the number of free parameters is determined by first calculating the number of total parameters using the following formula:

$$\text{\# total model parameters} = \frac{p(p+1)}{2}$$

where p is the number of observed variables. Then to obtain the number of free parameters, we need to subtract the number of estimated parameters from this number. Estimated parameters include factor loadings, error variances, and intercorrelations.

Following this guideline, for example, the sample size needed for a simple confirmatory factor analysis (CFA) with two correlated factors (φ_{21}), each of which has three continuous factor indicators and the following *a priori* proposed factor loading $\Lambda = [\lambda_{11}, \lambda_{21}, \lambda_{31}, \lambda_{42}, \lambda_{52}, \lambda_{62}]$ and error variance $\Theta = [\theta_{11}, \theta_{22}, \theta_{33}, \theta_{44}, \theta_{55}, \theta_{66}]$ matrix structures to be estimated, would be equal to

$$\text{\# total model parameters} = \frac{p(p+1)}{2} = \frac{6(6+1)}{2} = 21$$

and the number of estimated parameters is:

\# estimated parameters = 6 factor loadings + 6 error variances + 1 factor intercorrelation

= 13

So, the total number of free model parameters is 21 – 13 = 8. Then to calculate the needed sample size, we multiply this number by 10. So

Sample Size Needed = # free parameters X 10 = 8 X 10 = 80.

However, number researchers have challenged universal applicability of this rule (e.g., Cudeck & Hensly, 1991; Jackson, 2003; MacCallum, Browne, & Sugawara, 1996; Muthén & Muthén, 2002). This is because the appropriate size of a sample depends on many factors, including the reliability of the variables, the strength of the relationship among the variables considered, the complexity and size of the model, the amount of missing data, and the distributional characteristics of the variables considered.

Fortunately, more precise methods exist. According to available literature, there appears to be two main methods for doing power analysis in SEM (cf. Kim, 2005). The first method introduced by Satorra and Saris (1985) and elaborated by Saris and Satorra (1993), computes power by the following steps:

(1) First, estimate the model of interest.

(2) Second, choose a fixed parameter whose power is desired.

(3) Third, re-estimate the initial model with each estimated parameter fixed at their estimated value and choose an "alternative" fixed value for the parameter of interest.

Note that if the null hypothesis is true for that parameter, then the likelihood ratio chi-square for the model would be zero with degrees-of-freedom equaling the degrees-of-freedom of the model. If the null hypothesis is false for that parameter, then the likelihood ratio chi-square will be some positive number reflecting the specification error incurred by fixing that parameter to the value chosen in the initial model. This number is the noncentrality

parameter (NCP) of the noncentral chi-square distribution, which is the distribution of the test statistic when the null hypothesis is false. This number can be compared to tabled values of the noncentral chi-square distribution to assess power.

Although widely used, this approach is not without limitations. Kim (2005) describes three specific limitations to the Satorra-Saris approach:

(1) A specific alternative model must be defined, which is not always easy.

(2) Not all possible alternative models can be tested due to the technical limitations that accompanies the nesting of the alternative model within the null hypothesis model; and

(3) It can only be used to compute power, and not the sample size needed to achieve a given power in a future study because it requires raw data.

Recognizing these limitation, Mooijaart (2003) and Yuan and Hayashi (2003) generalized the Satorra-Saris method by utilizing a bootstrap approach. Again, like the original Satorra-Saris method, a raw data set is required to be able to implement the bootstrap. However, the benefit of these modified approaches is that these methods can be used with non-normal as well as missing data. Also, an empirical distribution of test statistics can be used for calculations, instead of a theoretical distribution, due to the bootstrap methodology (Kim, 2005). Muthén and Muthén (2002) solved the problem of a raw data requirement by implementing the Satorra-Saris method through a Monte Carlo study. This method, like the Yuan-Hayashi method described previously, can be used with non-normal and missing data. However, their estimate of proposed sample size is only as good as the parameter estimates used in its computation. If the parameter estimates are incorrect, the power and proposed sample sizes will be incorrect as well (Kim, 2005).

The second approach was introduced by MacCallum, Browne, and Sugawara (1996). According to their method, the power is computed by redefining the H_o in SEM in terms of the root mean square error of approximation (RMSEA) rather than Σ. The population RMSEA is defined as:

$$\varepsilon = \sqrt{\frac{F(\Sigma, \Sigma(\theta))}{df}}$$

where Σ is the true population covariance matrix and Σ(θ) is the population covariance matrix under the null hypothesis. The H_o in SEM is Σ = Σ(θ) and the alternative hypothesis (H_a) is Σ ≠ Σ(θ). Unlike the Satorra-Saris method, note that the alternative Σ_A is not required in this method. MacCallum et al. (1996) created three different H_o and H_a :

(2) Not close fit, H_o: ε ≥ .05 and H_a: ε < .05;

(3) Close fit, H_o: ε ≤ .05 and H_a: ε > .05; and

(4) Exact fit, H_o: ε = 0 and H_a: ε > 0.

Using the following values for ε:

(1) Not close fit, ε_0 = .05 and ε_a = .01;

(2) Close fit, ε_0 = .05 and ε_a = .08; and

(3) Exact fit, ε_0 = 0 and ε_a = .05;

MacCallum and colleagues computed two noncentral χ^2 distributions, the first according to ε_0, which yields a noncentrality parameter $\delta_0 = (N - 1)/df\varepsilon^2_0$ where *df* is the degrees of freedom and *N* is the sample size, and second, according to ε_a which yields a noncentrality parameter $\delta_a = (N - 1)/df\varepsilon^2_a$. These are obtained from $\delta = (N - 1)F(\Sigma, \Sigma(\theta))$ (see Appendix 3 for a table of these values). MacCallum and Hong (1997) extended this approach to allow the

use of the Goodness-of-Fit index (GFI) and the Adjusted Goodness-of-Fit Index (AGFI) instead of RMSEA.

The problem with the MacCallum and colleagues' approach, however, is that only one goodness-of-fit statistic is used. Using different fit statistics can lead to different conclusions. For example, MacCallum and Hong (1997) showed that the power computed using RMSEA and AGFI increased as degrees of freedom increased; however, the power computed using GFI had the opposite effect. Kim (2005) explains this contradictory finding and proposes an alternative method that allows the use of multiple goodness-of-fit indices.

Kim (2005) argues that since the noncentrality parameter (δ) is usually unknown in practice and that meaningful values of δ are hard to know *a priori*, new procedures for computing δ are required. According to this new procedure, Kim (2005) proposes, δ can be computed using fit indices such as Comparative Fit Index (CFI; Bentler, 1990), RMSEA (Steiger & Lind, 1980), McDonald's (1989) fit index, and Steiger's (1989) γ.

The basic approach for computing a proposed sample size for each of these fit indices follow the same initial three steps:

(1) Identify a SEM model.

(2) Compute the degrees of freedom (*df*) for the model.

(3) Compute the noncentrality parameter, $\delta_{1-\beta}$. (see Appendix 3B).

For example, for a three-factor, nine-variable CFA model ($p = 9$). The degrees of freedom (*df*) for this model is 24. Examining Appendix 3B, we see that the noncentrality parameter $\delta_{1-\beta}$ for power =.80 is 22.486. (For *df* (or power) not in the table, Kim (2005) provides syntax for SPSS and SAS algorithms for obtaining the noncentrality parameter $\delta_{1-\beta}$.).

Using this value, we can calculate the proposed sample size for using each fit index. For example, using the RMSEA fit index, we first need to specify ε = .05. So, using *df* = 24, $\delta_{1-\beta} = 22.486$, and ε = .05, we can calculate the proposed sample size by plugging in these values into the following equation:

$$N_{\varepsilon} = \frac{\delta_{1-\beta}}{\varepsilon^2 df} + 1 = \frac{22.486}{.05^2(24)} = 376$$

So, the proposed sample size using the RMSEA fit index is 376. In the same way, sample sizes are computed using the appropriate formula for each fit index (see Appendix 3C). However, note that proposed sample sizes will differ depending on the fit index used. Kim (2005) warns that the different proposed sample sizes are due to different levels of misspecification in the model and not due to the different characteristics of the fit indexes. They should produce the same proposed sample size given the same level of misspecifcation (Kim, 2005).

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